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Essays on the application of behavioural insights to environmental policy

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Abstract

While it is no longer a debate whether behavioural insights are important to environmental policy, a deeper understanding of how to *best* use them in order to efficiently inform interventions is still needed. The works compiled in this thesis are concrete examples of how methods, insights and evidence from behavioural science and economics could enlighten policy makers wishing to understand and reinforce pro-environmentalism. The first part (Chapters 1 & 2) is a direct application of methods and insights from psychology to environmental public policy. It is the product of a collaboration with policy makers in the French Parisian region, to tackle two polluting behaviours: littering and household combustion. The first chapter shows how laboratory experiments using psychometric methods from vision research could be crucial to inform policy makers on how to maximise the effectiveness of littering interventions, by quantifying the increase in visual salience following a change in the colour of trash bins in an urban setting. The second chapter, using a field experimental setting, shows that while information provision is not enough to change household combustion behaviour, increasing the salience of indoor pollution by combining feedback provision and social comparison is effective in changing behaviour and decreasing indoor air pollution. The second part of this thesis (Chapters 3 & 4) examines the relationship between socioeconomic status and the psychological mechanisms underlying pro-environmentalism and behavioural interventions. The 3rd chapter shows that the positive association between socioeconomic status and pro-environmental attitudes is partially mediated by individual time preferences. Chapter 4 is a short review suggesting that socioeconomic backgrounds could moderate the effectiveness of popular environmental behavioural interventions -such as defaults, social comparisons and commitment devices- that leverage on biases likely to be heterogeneous across income groups.

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Introduction

Humans shape the environment surrounding them. We extract water to drink, cut down forests to eat and heat, release air pollutants to travel and improperly discard cigarette and plastic waste in nature. Rapid population, economic and globalisation growth have driven up the demand for resources and the production of pollution and greenhouse gas emissions to a very high and unsustainable rate, dramatically affecting entire ecosystems and dangerously warming up the planet. Recent studies estimate that 75% of the Earth's land and 66% of the ocean has been profoundly changed by human activity, threatening more species with global extinction now than ever before (Díaz et al., 2019). The consequences of man-made climate change on humans themselves, such as extreme weather conditions and destruction of livelihoods, are mostly borne by already disadvantaged populations. In 2019 alone, weather-related hazards triggered 24.9 million refugees in over 140 countries, disproportionately affecting the most vulnerable (Brondizio et al., 2019). These consequences are expected to exacerbate as the size and wealth of the world population continue to grow, and despite recent efforts to reverse these trends, we are not on the right path. On the current track of carbon dioxide emissions, the planet's temperature is foreseen to rise by 3 to 5 degrees Celsius by the end of century, well above the 2 degrees Celsius targeted by the international community to prevent catastrophic events (Masson-Delmotte et al., 2018).

The plan put forth in the recent Intergovernmental Panel on Climate Change report

as well as models projecting alternative scenarios to limiting global temperatures (Van Vuuren et al., 2018) draw attention to the indispensable role of lifestyle and behavioural changes, such as reductions in meat diets, household heating and cooling and individual transport. As such, even though structural changes are needed, it is now widely accepted that modifying individual behaviour is essential for addressing environmental challenges.

Understanding human psychology helps us understand why humans damage nature. Psychological but also structural, economic and political factors explain why it is common for humans to deteriorate the environment that ensures their survival and why it has been hard to reverse this pattern despite increasing awareness. Economic theory suggests that in the face of externalities and public good properties linked with environmental issues - such as the absence of property rights and market prices - markets fail to regulate environmental exploitation. As such, individuals' welfare maximisation problem often fails to coincide with that of society.

Research in environmental psychology proposes further potential psychological barriers to environmentally friendly behaviour, even in the presence of perfect information and a willingness to protect the planet. In fact, a main feature of environmental matters is the asymmetry in benefits and costs; the benefits of consuming resources are very palpable, immediate and happen at a local level. The costs, however, are often invisible, occur in a distant future and are far away geographically. In parallel, humans have developed cognitive biases throughout years of evolution - such as salience, present and optimism biases - that might lead them to make a sub-optimal choice for themselves or for society today when they are faced with these asymmetries. For example, the salience bias describes our tendency to have a bias in favor of the salient and visible features of the decision making process (Hirshleifer, 2008). This is why, the vivid and tangible aspects of eating

a good hamburger, such as its taste, easily overshadow its scattered and hard to measure associated environmental costs, such as the deforestation of the Amazon forest, the cows' methane production and the use of large quantities of water. The present bias is another related psychological barrier that might stand in the way of pro-environmental behavior. In fact, we often prefer immediate rewards compared with future ones. As such, we discount future benefits at a very high rate and overweight short-term considerations (Loewenstein and Prelec, 1992). We observe individuals do so when making health and economic decisions, but it is particularly relevant in the environmental context, one that suffers large intertemporal trade-offs; cutting individual carbon emissions by limiting car use implies self-restraint in the present, in order to maintain decent life conditions for future generations or for oneself in the future. Finally, we might have strong biases related to the assimilation of information. Optimism bias, for example, leads us to believe that compared to others, we are less likely to suffer a bad outcome and more likely to encounter a positive outcome. This drives us to underestimate the real individual risks of environmental hazards, such as hurricanes and droughts, even when it is successfully communicated to us (Gifford et al., 2009). Therefore, policy responses to such a complex issue require a mix of policy tools inspired from different disciplines, and the study of human behaviour is a central one.

Understanding human psychology can also help develop more effective policy to counteract this individual and collective failure in taking pro-environmental action. In fact, people respond not only to incentives, information and persuasion, but also to how these interventions are designed, framed and communicated (Kahneman, 2011). Specifically, environmental psychology research can be relevant in understanding the impact and acceptability of traditional economic interventions, such as taxes and subsidies (McCaffery and Baron, 2006; Finkelstein, 2009). For example, it has been

suggested that individuals may be far more willing to pay for a green compensation fee when it is called a "carbon offset" instead of a "carbon tax", especially if they identify as Republicans or Independent on the political spectrum (Hardisty, Johnson and Weber, 2010). Information provision tools could also be better adapted to bridge the persistent knowledge-action gap in environmental action. Meta-analyses generally find great heterogeneity in the effectiveness of information provision (Andor and Fels, 2018*b*; Karlin, Zinger and Ford, 2015), suggesting that the content and format of the information matter a lot for its effectiveness. For instance, evidence shows that people's loss aversion makes informational incentives more effective when the potential losses to the environment are highlighted rather than the potential gains (Ghesla et al., 2020). Other non-monetary interventions, such as the provision of high frequency feedback through smart electricity and water meters, were put in place to overcome the salience and present bias facing resource consumption decisions. Such interventions are believed to increase the salience of environmental costs in the present. Providing people with their real-time water consumption profile while showering reduced water consumption by 11% in hotel rooms and by 22% at home (Tiefenbeck et al., 2018, 2019). Another well documented contribution to environmental incentives relates to the importance of social norms when making decisions. We know that humans tend to imitate others; households are more likely to take up photovoltaic panels if their neighbours do so (Bollinger and Gillingham, 2012) and individuals are more likely to litter in environments where people already littered (Keizer, Lindenberg and Steg, 2008). This inspired a large number of behavioural interventions based on social comparison that proved effective in encouraging resource conservation, sometimes equivalent to important increases in prices (Ferraro and Price, 2013; Allcott, 2011). Finally, environmental psychology can help anticipate or avoid backfire effects of some mitigation measures. For instance, we now know that incentives to recycle should be accompanied with

incentives to consume less because people tend to produce far more waste when the possibility of recycling attenuates part of the guilt associated with usage (Catlin and Wang, 2013).

The first part of this thesis adds to this literature by providing more evidence on the effectiveness of behavioural insights in decreasing pollution. Chapter 1 explores psychometric methods used in psychology to inform urban littering policy from the lab and chapter 2 provides field evidence on how increasing the salience of pollution through smart meters and providing social comparison could be more effective than generic information provision in decreasing household polluting behaviour.

Chapter 1: Informing anti-littering policy using a laboratory setting

Littering is an important challenge for local authorities and maintaining a clean public environment is actually often reported as a top priority for residents. This puts pressure on municipalities to increase already sizeable yearly budgets devoted to cleaning, and to maximise the effectiveness of the strategies that are already in place to prevent littering behaviour. One of the available options for authorities is to increase the number of bins in the urban space, a factor that has been shown to decrease the probability of improper waste disposal. An alternative intervention is to increase the visibility of existing bins. Such low-cost design interventions indeed have the potential to elicit involuntary attention, thereby increasing the perceived number of bins. This study is a telling illustration of the way in which laboratory-based experiments can work as an important first step before heading to the field; we estimate how much a change in trash-bag colour increases trash can visibility in Paris. To that end, we apply standard Signal Detection techniques to test how much

changing trash-bag colour from grey to red affects subjects' detection rates. In three pre-registered studies (total N = 922), we find that changing trash bag colour from grey to red translates into a 28% increase in the perceived number of bins. This means that a zero-cost change of trash-bag colour from grey to red is equivalent to installing 8,400 additional bins in the city of Paris, in terms of perceived density. Replication studies investigating additional colour changes show that changing the colour from grey to blue further increases visibility, with blue exhibiting the highest increase in visibility in a sample living in the Paris area compared to a same of UK residents.

Chapter 2: Decreasing air pollution using feedback in a field experiment

In this chapter, we address another avoidable polluting behaviour: occasional household combustion. In fact, exposure to air pollution is one of the leading causes of morbidity and mortality worldwide and is largely determined by household behaviour. Yet, the sources and impacts of indoor air pollution are still largely misunderstood and misperceived by the public. For example, although occasional wood burning in an extremely polluting activity to users and is responsible of more than 40% of particle pollution in Europe, it is associated with a distorted perception and considered to be a low-polluting, natural and healthy activity. The same pattern is observed with candle and incense burning, two important sources of indoor PM2.5.

As discussed above, overcoming salience bias by providing feedback as well as leveraging social influence by providing social comparison were proven successful in decreasing resource consumption. In this chapter, we wanted to test whether a combination of these tools is effective in changing combustion behaviour, and whether it is more effective than a generic informational campaign. To that end, we equipped 281 households with micro-monitors and assigned them to three conditions: the

Information treatment, the *Information + Personalised Emission Profile* treatment, and the control group. The *Information* treatment consisted of weekly leaflets containing generic health-framed information on the risks related to indoor air pollution and multiple combustion activities, with special attention to wood burning. In contrast, households in the *Information + Personalised Emission Profile* treatment were sent the same generic information plus a weekly Personalised Emission Profile of their indoor pollution levels, consisting of the graph of precise meter readings of the concentration of PM2.5 measured every five minutes over the last week, as well as statistics to compare their emissions to the emissions of similar households (in fact, the control group). We find that the *Information + Personalised Emission Profile* treatment was successful at decreasing indoor levels of PM2.5, a proxy of household polluting behaviour change, with a sustained and significant decrease starting on the 3rd week after the beginning of the intervention. Heterogeneous impact analysis reveals that the effect is concentrated in the most polluted households. For that group, the number of days over the WHO 24-hr limit -not to be exceeded more than 3 days per year- decreased by 52%, from 12.4 down to 5.9 days over the study period. In contrast, we observed no change in indoor air quality for households receiving the *Information* treatment, suggesting that generic information about the health risks of combustion activities is not sufficient to induce behavioural changes. These results may be of particular interest for policymakers in a context where micro-sensor technologies that detect ambient PM2.5 levels are increasingly available and affordable.

To understand the mechanisms behind these results, we collected data on household's perception, knowledge and attitudes on indoor polluting sources. We find that both interventions were successful at increasing the perceived detrimental impact of wood burning and smoking on indoor and outdoor air pollution, and at decreasing declared frequency of wood burning in the future. We find no evidence of an impact on

pollution health risk perception, attitudes toward wood burning regulation, pleasure when lighting a fire, nor on the intention to change wood burning equipment in the future. Declared frequency of combustion activities was not different between the control group and both treatment groups, as well as air quality improving activity, which is at odds with the objective reduction in PM2.5 concentration observed by micro-monitors. This chapter makes several contributions to the literature. First, it adds to the limited evidence on the use of smart meters to change behaviours. Second, it provides evidence - still scarce in the literature- on the superiority of tailoring information in changing behaviour, compared to generic communication. But very few studies compare one against the other, and both against no information, as we do in this paper. Finally, this result further enriches the literature on the awareness–behaviour gap, whereby individuals are aware of an issue, like climate change, air pollution, or the importance of preventive behaviours, but fail to undertake concrete actions.

Humans shape the environment surrounding them but the physical environment shapes human psychology, too. The environment in which people grow up and live shapes their behaviour and changes to the physical environment can have significant effects on their actions. People care more about climate change and donate more to environmental causes when local temperatures are high (Li, Johnson and Zaval, 2011) and unconsciously produce less litter when exposed to the smell of lemon, following a cognitive route from olfactory perception to behaviour (Holland, Hendriks and Aarts, 2005). Ecology has further deeper impacts on preferences. Children who grow up spending more time in nature behave more pro-environmentally in adulthood (Chawla and Derr, 2012).

The second part of this thesis focuses on another source of heterogeneity in ecology;

deprivation. In fact, poverty and harsh economic conditions deeply affect people's psychology, preferences and strategies (Haushofer and Fehr, 2014). Individuals living in environments with shorter time horizons might choose to invest even less than others in future outcomes, which may in turn lead them to invest less in conservation behaviour. The 3chapter of this thesis explores this mediating hypothesis to try to explain the negative correlation between socio-economic status and pro-environmentalism. Finally, we believe that people living in environments characterised by deprivation may also react differently to public policy. The 4þchapter is a review of the effect having less resources can have on cognitive mechanisms underlying the success of behavioural interventions, and how that may lead to their heterogeneous effectiveness.

Chapter 3: The impact of socioeconomic status on environmentalism

As mentioned above, future-oriented individuals tend to display more pro-environmental attitudes and behaviours, compared to those who are present-oriented. Investigating the determinants of time preferences could therefore shed light on factors that also influence environmentalism. A key factor that impacts time preferences is socioeconomic status (SES). Importantly, SES is also positively correlated with willingness to act for the environment. In this paper, we test whether time preferences partially mediate the relationship between SES and pro-environmentalism in three studies. In the first study, we tested the assumption that pro-environmental attitudes are positively correlated with SES on a large cross-sectional French sample. We found expected results both with an objective and a subjective measure of SES. Then, we conducted an online study including a temporal discounting task, which allowed us to fully test the mediation hypothesis on British participants. Our results

suggest that the positive association between SES and pro-environmental attitudes is partially mediated by temporal discounting, but no significant mediated relationship was found for pro-environmental behaviour. Finally, to test for a causal relationship, we conducted a laboratory experiment inspired by previous research showing that it is possible to use information about income as an experimental treatment, so as to alter the perception of one's socioeconomic condition. In this experiment, we recruited only participants who underestimate their position in the income distribution. In the treatment group, participants received a correction of their misperception, in order to increase their perceived relative income while the control group received no intervention. The participants then answered a time discounting task and questions measuring pro-environmentalism. Although the expected shift towards increased preferences for the future was not observed, we found a moderated effect of the treatment on pro-environmentalism.

Chapter 4: The impact of income on the effectiveness of behavioural interventions

If we believe that different ecologies produce different cognitive strategies, should we expect lower-income households to react differently to behavioural public policy leveraging cognitive biases? The effectiveness of choice architecture is well documented, but much less is known about its potential distributional consequences. In this chapter, I review three of the most documented interventions in environmental public policy: goal setting, default options and social comparison. I examine how the cognitive biases and levers underlying their efficacy, such as future orientation, inertia bias and social conformity, vary across income levels and review the evidence on the heterogeneity of their effects in the literature. I find that, although robust

evidence is still scarce in the environmental context, behavioural public policy could have unintended distributional effects and worsen existing social disparities. Further research would attempt to explore and fill the gap in the literature on the heterogeneous and distributional effects of behavioural interventions, notably generic social norm messaging.

Chapter 1

A zero-cost attention-based approach to promote cleaner streets: Signal Detection Theory in Parisian streets*

1.1 Background

Littering and improper waste disposal in public spaces is an important challenge for communities and local authorities. Maintaining a clean public environment is actually often reported as a top priority in large and touristic cities. In Paris' latest participatory budget poll, Parisians allocated the highest number of votes to a project aiming to improve "the living environment through more efficient cleaning of the city" (Maviel, 2018). This has put pressure on the municipality to increase an already sizeable yearly budget of €600 million devoted to keeping the city clean and maximise

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the effectiveness of strategies that are already in place to prevent littering behaviour.

Littering is a social problem that not only creates aesthetic damages and exhausts a substantial share of public funds, but it also carries important environmental, physical, and psychological costs (Slaughter et al., 2011; Shenassa, Liebhaber and Ezeamama, 2006; Ellaway, Macintyre and Bonnefoy, 2005; Blackman et al., 2001). For instance, cigarette butts which are by far the most littered item around the globe - with approximately 15 billion cigarettes improperly discarded in nature every day - are a major source of land and aquatic pollution that can have dramatic toxic effects on entire ecosystems (WHO, 2017; Novotny et al., 2009; Healton et al., 2011). The presence of litter in the urban environment can also deepen existing economic and health inequalities by depressing local investment or discouraging outdoor physical activity in highly littered neighbourhoods (Blackman et al., 2001; Balfour and Kaplan, 2002). Experimental evidence also confirms that even small amounts of litter can induce a rise of antisocial behaviours ranging from further degradation of the living environment to more serious crimes, such as theft (Keizer, Lindenberg and Steg, 2008).

Many empirical studies that have focused on understanding and preventing the widespread prevalence of littering as early as in the 1970s have confirmed that sites with more receptacles tend to have lower littering rates (Geller, Witmer and Tuso, 1977; Schultz et al., 2013; Nkwocha and Okeoma, 2009; Finnie, 1973). A multilevel analysis identifying the predictors of littering confirmed that, after controlling for a large number of individual level variables, 15% of littering is still due to some aspect of the physical surroundings, such as the presence or absence of waste receptacles and how conveniently placed they are (Schultz et al., 2013). A large increase in the number of trash bins therefore has the potential to trigger notable adjustments in behaviour by removing seemingly small barriers hindering proper waste disposal. In an effort to decrease litter in the streets of Paris, 30,000 bins were deployed by the

local authorities in 2013.

However, one issue with this policy is that increasing the number of bins is costly due to the cost of the bin itself, its installation and the added manpower needed to collect trash from additional locations. In Paris, the 30,000 added bins in 2013 cost €2million, not including collection costs[2]. Despite the important effort, this policy was not sufficient to solve the littering problem. Auditing authorities then recommended yet another increase in the number of bins, raising concerns about the congestion of public space (MIE, 2018).

In this study, we test whether an increase in the visual saliency of bins can work as a cost-effective substitute to adding bins by increasing the perceived density of bin availability in a city. Indeed, making trash containers more attractive or noticeable has been suggested as an alternative to adding bins in a number of studies. Current evidence shows that a more visible bin is more used, regardless of its positioning, which suggests that increasing saliency can be an effective policy to decrease littering (Arnold, 2015; Geller, Brasted and Mann, 1980; O'Neill, Blanck and Joyner, 1980). This solution appears particularly promising in cities where policy makers strive to keep streets charming and deliberately favour designs that make bins blend with the surrounding urban environment. In Paris, for instance, public trash bins are made of a light grey metal and fitted with discreet grey bags, which means that they are essentially designed to be invisible and to blend in with the urban space (Figure 1.1).

Scientists studying vision have long noted that attention can be modulated in two-ways: endogenously and exogenously. Endogenous attention relies on "top-down", goal-driven mechanisms, leading the individual to voluntarily seek out information in the environment. Exogenous attention is stimulus-driven and refers to processes

[2] Paris : nouveau design pour les poubelles parisiennes. (2013, November 27). France Info. Retrieved from https://france3-regions.francetvinfo.fr/paris-ile-de-france/paris/paris-nouveau-design-pour-les-poubelles-parisiennes-366167.html

Figure 1.1: An example of one of the 30,000 trash bins deployed in Paris since 2013

that automatically lead salient stimuli to attract attention, through "bottom-up" mechanisms. Exogenous attention is also referred to as bottom-up salience and typically emerges from contrast differences between objects and their surroundings; for example, if the colour of an object is particularly salient compared to the background against which it stands. Multiple studies have indeed shown that salient colours elicit rapid and involuntary attention shifts to the object, regardless of whether subjects had an internally generated (endogenous) motivation to orient their attention to that specific object (Schreij, Theeuwes and Olivers, 2010).

Interventions in litter control, such as ex-ante campaigns reminding individuals of littering costs or high fines that punish uncivil behaviour ex-post, might increase endogenous attention and trigger top-down visual search to find the closest bin. Interventions aiming at increasing the salience of bins relative to the surroundings will, on the other hand, trigger automatic attentional capture to the bin. Such an intervention could take the form of a simple change of trashbag colour from grey to more salient colours, leading to an increase in the *perceived* number of bins.

Using a signal detection task applied to modified photographs of Parisian streets, we measure the impact of a simple change in trash-bag colour on bin detection. We then convert the effect to a measure of perceived trash density and approximate the

equivalent number of real bins that would have to be added in the streets of Paris to achieve the same effect. We then replicate the results with different colours, and a different target population.

1.2 Study 1

In order to quantify the increase in detectability of trash bins following a change in bag colour from grey to red, a colour that has been reported to be the most salient in a number of vision studies (Gelasca, Tomasic and Ebrahimi, 2005; Etchebehere and Fedorovskaya, 2017), we ask participants to detect the presence or absence of a bin in photographs taken in the streets of Paris, with half of them containing a bin and the other half not containing a bin. We then measure the difference in detection accuracy between the two trash bag colour conditions, using Signal Detection Theory parameters.

Methods

Material

Photographs. The visibility of a colour signal in a given environment depends greatly on characteristics of that environment such as the background colour, the brightness and amount of ambient illumination (Reynolds, White and Hilgendorf, 1972). 50 unique photos[3] in the initial grey bin condition were taken in Parisian streets to span a variety of settings (brightness, contrast, number of distractors, positioning of the bin, etc.). In order to ensure comparability between the different conditions (grey-

[3]In order to select these 50 photos we first ran a pilot study on 100 participants with a set of 100 photos, only testing the grey condition. This allowed us to calculate a measure of detectability for each photo in the baseline condition and pick the 50 photos exhibiting bin discriminabilities that were neither too low nor too high. We set the display time to 700ms after noticing that the task appeared to be very hard (accuracy of detection was really low for most participants) for a shorter display time of 500ms.

bag condition, red-bag condition, no-bin condition) and eliminate potential biases related to the object's visibility,we created three versions of each photograph using Adobe Photoshop: 1) a grey-bag version with the original photograph of the bin fitted with its original grey bag (grey bag condition) 2) a red-bag version with the same bin edited to be fitted with a red bag (red bag condition) 3) and a no-bin version with the same photograph edited to have no bin (no-bin condition). When producing the different versions of the stimuli, we altered the hue of the bag but did not change the contrast. Figure 1.2 (Panels a-c) shows an example of the 3 versions of the same photograph.

Questionnaires. We also collected socio-demographic variables (age, sex, income level and educational attainment) and included standard questions used in visual tasks (self-reported colour blindness, self-reported use of glasses or contacts) to assess our sample's representativeness.

Figure 1.2: Example of a displayed image in the three possible conditions

(a) Original image, grey-bag condition

(b) Photoshopped image, red-bag condition

(c) Photoshopped image, no-bin condition

Design and procedure

The pre-registered[4] experimental task was hosted on the online research platform Prolific Academic and programmed using JavaScript in Qualtrics. Participants were asked to use a full-screen mode on a computer to complete the task, which lasted between 8 and 15 minutes. The same image was seen 4 times by each participant; once in the grey-bag condition, once in the red-bag condition and twice in the no-bin condition. Each participant therefore saw the 200 photographs in a random order. Of these 200 stimuli, 100 contained a trash bin (50 in the red-bag condition and 50 in the grey-bag condition) and 100 contained no bin (each of the 50 photographs containing no bin was presented twice). The 200 trials were split into three blocks separated by two breaks. Both the order of the blocks and the order of the pictures within each block were randomised. In each trial, the picture was flashed in the centre of the screen for 700 ms. We used a short display time rather than a display time allowing for visual search because our goal was to focus on automatic and rapid attentional processes (Handy, Kingstone and Mangun, 1996; Hawkins et al., 1990). Subjects in a visual search task make multiple fixations and saccades, with each fixation lasting between 200 to 500 ms approximately (Hooge and Erkelens, 1998). This means that the chosen presentation time of 700 ms gives our participants enough time to perform only two to three fixations. Given the complexity of the visual scenes participants were presented with, participants would not have had enough time to fully scan the scene in a top-down fashion.

Participants were then asked to indicate whether they saw a bin or not at the end of each trial, using letters on their keyboard. Both responses and reaction times were recorded. In addition, 20 catch trials were included to screen out participants who were not paying attention during the task. In these trials, participants saw photographs with easily detectable bins that were displayed long enough (1 second)

[4] https://osf.io/q7fyd

to make the answer trivial. Questionnaire data was collected at the end of the experiment.

Participants

Keeping in mind that touristic neighbourhoods in Paris are more littered than non-touristic ones, we focused on a non-Parisian sample, i.e. people who are not familiar with the format of bins in Paris. Considering that the highest number of tourists in the city comes from the United Kingdom (Gidrol and Heim, 2019), we recruited 324 British participants through the online platform Prolific Academic. All participants received a compensation of £7.5 per hour. We pre-screened participants using Prolific's approval rating; participants with approval ratings below 95% were screened out. We excluded 15 subjects who performed at or below chance in the catch trials[5]. Trials for which reaction times were too short (150 ms or less) or too long (4000 ms or more) were also excluded. After making sure that no participant had more than 30% missing trials, 309 participants remained in the final analysis (204 females, 104 males, mean age: 36.96 +/- 12.7 years), a large enough sample to be detect a minimum effect of 10%[6].

Analysis

Our study's analysis plan relies on Signal Detection Theory in order to quantify the change in salience resulting from a change in bag colour. Signal Detection Theory is used to measure participants' ability to discriminate between a target stimulus and irrelevant noise (Macmillan and Creelman, 2004).

In Signal Detection Theory, participants' responses are classified into one of the following four categories: hits, misses, false alarms and correct rejections. In the

[5]Chance threshold for 20 trials is 14 hits. A more conservative threshold of 18 hits out of 20 yields comparable results and conclusions.

[6]With 95 confidence level and a power of 80%. The variance of the outcome was calculated using the data collected in the pilot study on 100 participants.

red-bag and grey-bag conditions, a "hit" is recorded when the participant detects the bin and a “miss” is recorded when the participant fails to detect the bin. In the no-bin condition, a “false alarm” is recorded when the participant detects a bin and a “correct reject” is recorded when the participant indicates that there is no bin. In this study, we are particularly interested in capturing changes in bottom-up attention in response to increased trash bag salience. We therefore focus on the discriminability d', a metric that allows us to capture earlier stages of visual processing such as the sensory encoding of stimuli. d' represents the strength of the signal relative to noise, which corresponds to participants’ ability to detect the bin. A discriminability d' of 0 means that the signal is not distinguished from noise, while higher d' values represent a stronger signal-to-noise ratio (i.e. a situation where it is easier for people to discriminate the bin in the scene). d' can thus be considered as an index of task difficulty. d' is calculated by subtracting z corrected false alarms from hits: $d'_c = z(H_c) - z(F_c)$ where H is the hit rate, F the false alarm rate and the subscript c the colour condition (“red” or “grey”) and $z()$ the normal probability curve. The difference between mean discriminability in the two colour conditions $d'_{red} - d'_{grey}$ will thus allow us to quantify the change in bin perception following a change from grey to red. Given that photographs containing the bin are identical to photographs not containing the bin, it is reasonable to assume equal variance of the noise and signal distribution across conditions.

However, participants exhibit a bias in their strategy to set a threshold over which they make the decision that the stimulus is present. This bias is measured by a second metric in Signal Detection Theory, the criterion, or ‘response bias’, C. It thus reflects a participant’s tendency to provide one type of response more frequently than the other. It is calculated as follows: $C_c = -\frac{z(H_c)+z(F_c)}{2}$. A criterion C with a value of 0 shows that the decision threshold is fixed at a level that generates equivalent rates of false positives and false negatives. C will be positive if there are more hits and false

alarms than misses and correct rejections.

Signal Detection Theory thus allows us to get a measure of discriminability d' while taking into account the response bias C (Theeuwes and Van der Burg, 2007; Handy, Kingstone and Mangun, 1996).

In the analysis, the false alarm and correct rejects rates calculated from the 100 no-bin photographs were then used in the calculation of both d'_{red} and d'_{grey}.

Results

d' was calculated for each individual, in each of the two colour condition. A paired t-test for repeated measures was then used to compare the average discriminability change between the two colour conditions. In line with our hypothesis, d' is 23% higher in the red bag condition (M = 1.65, SD = 0.71) than in the grey bag condition (M =1.34, SD = 0.62), t(306)=15.59, $p < .001$. Moreover, mean reaction times to detect the bin are lower in the red-bag condition (M = 1076, SD = 283) than in the grey-bag condition (M =1113.9, SD = 286), t(308)=-8.8603, $p < .001$. Both accuracy and speed increase in the colour condition, which is consistent with an exogenous attentional effect.

Measuring and taking into account the sample's criterion C, we calculated that the observed d' increase in the red-bag condition translates into a maximum hit rate change of 29% (see Appendix for calculation). Keeping in mind that there are around 30,000 bins in Paris, this result suggests that changing the trash bag colour from grey to red would amount to adding 8,370 bins in the city. Given that the production and installation of one additional bin costs the municipality €150 (under conservative estimates), achieving with additional bins the same visibility increase as the one obtained by changing the bag from grey to red would cost local authorities around €1,250,550.

1.3 Study 2: Replication study with additional colours

While the results of the previous study show that red increases bin visibility, we thought it would be interesting to apply the same tool to different colours that have been considered by the municipality of Paris, namely green and blue. It can be noted that green bags were used by the city from 2013 up until 2019 and were then replaced by grey bags for aesthetic reasons. Blue has been proposed as a possible alternative colour.

Using the same experimental methods employed to identify the change in visibility when changing bins from grey to red, study 2 was run to investigate the effect of a change of colour from grey to green on bin visibility (study 2.A) or grey to blue (study 2.B). Figure 1.3b show the same of a photograph with different colours conditions. These two replication studies were pre-registered[7].

Figure 1.3: Example of a displayed image in Studies 2.A and 2.B

(a) Modified photograph in the green-bag condition

(b) Modified photograph in the blue-bag condition

[7] https://osf.io/48cs3

Participants

312 British participants were recruited for Study 2.A and 315 for Study 2.B through the online Platform Prolific Academic and received a compensation of £7.5 per hour. Participants were pre-screened to have a 95% or above approval rating. 7 subjects who performed at or below chance in the catch trials were excluded from the analyses of each study. Trials for which reaction times were too short (150 milliseconds or less) or too long (4000 milliseconds or more) were also excluded. After making sure that no participant had more than 30% missing trials, 305 participants remained in the final analysis for Study 2.A (175 females, 130 males, mean age: 35.7 +/- 12.2 years) and 308 (202 females, 106 males, mean age: 36.7 +/- 12.3 years).

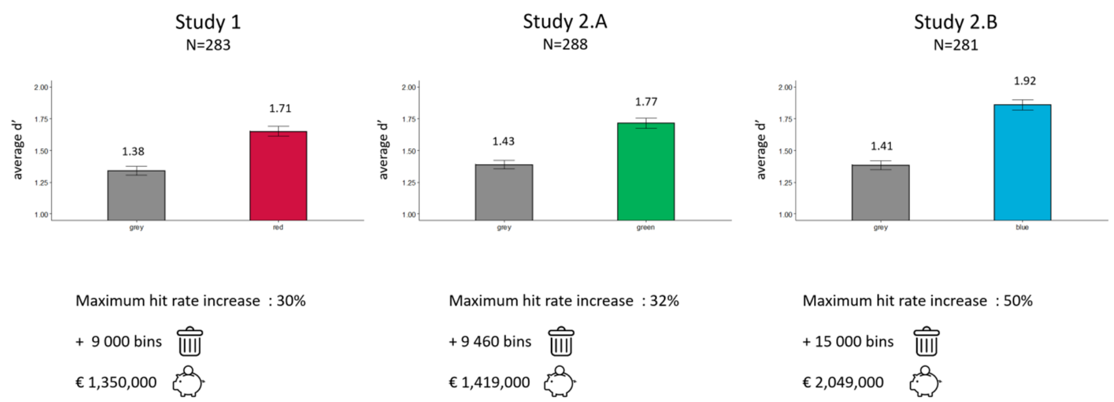
Results

d' is 24% higher in the green-bag condition (Study 2.A, N= 300) (M = 1.73, SD = 0.69) than the one observed in the grey-bag condition (M =1.40, SD = 0.58), t(304)=18.596, $p < .001$. Maximum hit rate calculations suggest that this change in d' corresponds to an increase in the visibility rate by 31%, equivalent to installing 9,537 grey bins in the city of Paris. This would have cost the local authorities €1,430,000. Study 2.B (N= 308) tests the visibility of the blue-bag condition and shows the highest increase in discriminability compared to grey out of the three tested colours; in the blue-bag condition, d' is 35% higher (M = 1.86,SD = 0.7) than the one in the grey bag condition (M =1.38, SD = 0.6),t(307)= 25.269, $p < .001$. This translates into an increase of 46% of trash can visibility, similar to the addition of 13,600 new bins, avoiding a cost amounting to €2,049,000. In both studies, mean reaction time was shorter ($p < .001$) in the coloured condition (Study 2.A : green RT = 1097.3 (SD= 279) vs. grey RT = 1141.3 (SD = 274) and Study 2.B blue RT = 1056.6 (SD=215) vs grey RT = 1006.4 (SD=211), which suggests that there is no speed-accuracy trade-off.

We performed a mixed-model ANOVA to compare the results obtained in Studies

1, 2.A and 2.B, using the change from grey to colour as a within subject factor and study number as the between subjects factor. We found significant COLOUR x STUDY interactions when comparing red (Study 1) to blue (Study 2.B) F(1, 615)=35.92 $p < 0.001$ and when comparing green (Study 2.A) to blue (Study 2.B) F(1, 610)=32.01 $p < 0.001$; but no interaction when comparing red (Study1) to green (Study 2.A), F(1, 611)=0.46061 $p = 0.4$. Figure 1.4 summarises the results from the three Studies.

Figure 1.4: Results of study 1 and replicated studies 2.A and 2.B.



Note: This figure shows the average d' calculated for each condition, the associated maximum hit rate increase and the equivalent number of bins needed to achieve the same perceived bin density in the city of Paris and the associated cost saving in each of the three scenario.

1.4 Study 3: Replication study with a Parisian sample

Would the observed changes hold in a sample of people more familiar with the bins? We replicate the study, this time restricting the sample to participants living in majority in the Paris area. The expected effect on a "Parisian" sample is ambiguous; on the one hand, participants more likely visiting Parisian streets frequently will

have a better top-down grasp of the shape and the location of the bin in the urban setting, and we expect them to be better at detect bins, regardless of their colour. This would lead to a more modest or null effect of the colour change. On the other hand, the effect of the novelty of the trash bag colour versus the one the residents are used to, might cause a greater effect on attention. While we purposefully used a non resident sample in the previous replications to target tourists and disentangle the actual increase in salience from the novelty effect that might wear out fast, it is still crucial to measure the effect on the population most likely to use the bin other than visitors in non-touristic areas of the city. The colour blue was tested against the colour grey, as it was the one that showed the most promising results in Studies 1 and 2.

Participants

310 participants living in the Paris area were recruited on the platform CrowdPanel and received a compensation of €16 per hour. Trials for which reaction times were too short (150 ms or less) or too long (4000 ms or more) were also excluded. After making sure that no participant had more than 30% missing trials, 283 participants remained in the final analysis (125 females, 158 males, mean age: 39.1 +/- 13.8 years).

Results

d' is 39% higher in the blue-bag condition (M = 2.04, SD = 0.85) than the one observed in the grey-bag condition (M =1.46, SD = 0.75), t(282)=30.03, $p < .001$). Maximum hit rate calculations suggest an increase in the visibility rate by 58%, equivalent to installing 17,379 grey bins in the city of Paris in terms of perceived density. Installing 17,379 new bins would have cost the city €2,606,850.

A mixed model ANOVA confirms that the effect of changing the colour from grey to

blue is greater when considering a sample of residents in the Paris Area (F(1,589)= 14.9, $p < .001$).

General discussion

Individuals are often meaningfully influenced by modifications in their environment, even ones that appear minor. One of the main propositions put forward in nudge theory is the importance of alterations to the physical environment, in order to align behaviour with individual and social goals (Thaler and Sunstein, 2009). Understanding how to enhance the visibility of waste bins therefore has the potential to ultimately favour better anti-littering policies with low-cost nudges.

The results of this study suggest that a mere change in the colour of bins can result in a cost-effective intervention that would increase their perceived density in an urban setting; a change of bag colour from grey to red, green or blue in the city of Paris is equivalent to installing 8,370 , 9,537 or 13,600 additional bins respectively. Interestingly, the increase in perceived density is even more dramatic in a replication on a Parisian sample, a population that is already familiar with the bin and its placement. Beyond the two samples used in our studies, it would be useful to examine a representative sample of the diversity of passersby in Paris. This is particularly relevant for high touristic areas that also suffer from high rates of littering.

Our results have important implications for policy-making: while changing the colour of bags is a zero-cost intervention, adding 8,370 new bins in order to achieve the same visibility as that of a red bin, for example, might cost Parisian authorities up to €2,049,000 in installation costs only, which represents a significant share of the 40 million euros that are spent every year in Paris to clean the streets and collect litter (excluding salary costs)(Métropole du Grand Paris, 2019). Beyond the sizeable monetary costs, changing the colour of bin bags as opposed to increasing their

number avoids overcrowding an already congested public space. Increasing *perceived* bin density, rather than *actual* bin density, may therefore be a cost-effective policy lever, particularly in cities with an already great amount of bins, and a persistent littering issue.

Our results also provide grounds for future work investigating whether increased visibility of bins has a down-the-road impact on littering behaviour. While our studies do not allow us to state whether changing bag colour would have an effect on real-life littering, prior research provides suggestive evidence that making bins more attractive or noticeable affects behaviour (Arnold, 2015; Geller, Brasted and Mann, 1980; O'Neill, Blanck and Joyner, 1980). For example, littering rates in a shopping mall were 40% lower around highly noticeable and beautiful trash bins than around unobtrusive ones (Geller, Brasted and Mann, 1980). In another experiment, a decrease in improper cigarette butt disposal was observed outside a university campus after replacing normal ashtrays by ones that were decorated and eye-catching (Cope et al., 1993). Some cities, like Copenhagen and Vienna, have opted for increased salience of bins and have recorded drastic positive results (MIE, 2018).

In all these cases, the bin is at the same distance in the eye-catching condition and in the control condition but littering rates are different. This suggests that bottom-up attention plays an important role in littering, perhaps because bottom-up attentional processes affect all passersby in a similar way, unlike less malleable determinants of littering, such as people's individual motivation to look for a bin. Using short display times, as in our studies, is an interesting method to capture such bottom-up mechanisms.

More generally, this paper is a telling illustration of how laboratory studies can provide insightful contributions to policy-making and constitute a first crucial step before conducting field experiments. Indeed, if a policy maker wants to increase the perceived density of bins, it would be inefficient to go straight to a costly field trial

comparing various bin colours. Similarly, it would be highly inefficient to rely only on intuitions. As a matter of fact, we asked a sample of 150 people on the platform Prolific academic to provide their intuition on what colour would be most visible: "Imagine you are in charge of making sure that bins in your city are highly visible. Which colour would you pick for the bins? Green, red or blue?". The most common answer was red (50%), followed by blue (32%) and green (18%). Our studies shows that blue is in fact the colour that best improves detectability of bins. Determining which colour is most likely to be salient in a particular city first in the lab can therefore be a crucial evidence-based first step before elaborating a field strategy.

The method we used can be easily taken up by policy makers in order to produce evidence-based decisions on how to increase the visibility of trash receptacles in urban settings. Based on insights obtained in a lab setting, decision-makers can then maximise the efficiency of a field intervention, evaluated with rigorous but often costly randomised controlled trials. For instance, our method could be replicated with a variety of bin shapes and colours to help identify the most effective choice before turning to large scale implementation or field trials. Well-designed lab research can provide crucial insight for policy and is often complementary to field research, but is still greatly underused in the domain of policy development (Lunn and Ní Choisdealbha, 2018).

1.A Appendix

Maximum hit rate calculation

The maximum hit rate increase ∂h associated with a given effect size g (the fraction of sensitivity increase obtained for colored bins relative to gray bins) from a baseline sensitivity d'_0 (obtained for gray bins) is computed as:

$$\partial h = max_c(\phi(d'_0.(1+g), c) - \phi(d'_0, c))$$

where $\phi(.)$ corresponds to the cumulative normal distribution, and c is the detection criterion. The rationale behind this measure is that the criterion c used by participants for the detection of bins in scenes presented for 700 ms may differ from the criterion used by pedestrians in real-life conditions. The maximum hit rate increase h thus corresponds to the maximum expected increase in detection rate associated with the observed increase in sensitivity.

Chapter 2

The Effectiveness of Personalised *versus* Generic Information at Changing Individual Behavior : Evidence from an Indoor Air Quality Experiment*

2.1 Introduction

Exposure to indoor and outdoor pollution is one of the leading causes of morbidity and mortality worldwide (Burnett et al., 2018; Landrigan et al., 2018; Lelieveld et al., 2020). Despite improvements in air quality over the past 10 years, 90% of European countries still record levels of particulate matter with an aerodynamic diameter smaller or equal to 2.5 µm (hereafter, PM2.5) above the ones set by the

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World Health Organisation (European Environment Agency, n.d.). It is currently estimated that an annual loss of 2 million years of healthy life can be attributed to indoor air pollution alone (Asikainen et al., 2016). In fact, given that residents in high-income countries spend more than 80% of their time in closed environments, exposure to air pollutants is largely determined by indoor air quality (Klepeis et al., 2001; Oar, Oriá and Ied, 2014).

In the absence of polluting activity, the concentration of PM2.5 inside is similar to that recorded outside. However, when household polluting sources are activated, indoor air quality can be up to 5 times worse than outdoor air quality (Ebner, Le Moullec and Weill, 2005). Therefore, household behaviour significantly impacts the quality of indoor air. The main indoor sources of PM2.5 are combustion activities, with the largest emissions resulting from cooking, tobacco smoking and wood burning (Wallace and Howard-Reed, 2002; Long, Suh and Koutrakis, 2000; Nasir and Colbeck, 2013; Frasca et al., 2018). Residential wood burning releases far more abundant and harmful volumes of pollutants than other sources such as car exhausts or cigarettes (Gras et al., 2002; Pryor, 1992; Chafe et al., 2015; Hoek et al., 2008; Molnar et al., 2005), even when using certified, high-efficiency equipment (Frasca et al., 2018). The way users operate a fire has a large effect on the amount of pollution generated inside and outside the home (Nussbaumer et al., 2008). Beyond the sanitary risks facing its users, residential wood burning is also a major source of outdoor pollution. While it provides only 3% of energy needs, it is responsible for more than 45% of PM2.5 concentration in Europe, which makes it the leading source of outdoor air pollution, above transportation and the industry (Amann et al., 2018).

Yet, the negative consequences of wood burning and other combustion activities are largely ignored. Wood, candles or incense burning is typically associated with positive feelings and considered as a low-polluting, natural, and healthy. This strong positive association distorts the perception of health and environmental risks, and

is an obstacle to household behaviour change (Hine et al., 2007). Bhullar et al. (2014) find that higher perception of wood smoke risk is indeed associated with higher support for wood burning regulation in Australia and a higher likelihood of switching to alternative heating. More generally, despite an increase in awareness regarding air pollution, the public still has a limited apprehension of factors influencing indoor air quality and effects on health (Boso et al., 2018; Daniel et al., 2020; Grange, Sommen and Host, 2012; Hofflinger, Boso and Oltra, 2019). Therefore, finding levers to restore an adequate awareness of the risks associated with wood burning and other household polluting activities may be a key environmental and public health policy.

This paper tests the effectiveness of two interventions aimed at raising households' awareness of the risks associated with wood burning and other indoor pollutants, and in turn changing their behavior and decreasing air pollution. Using a randomized controlled trial in France, we equipped 281 households with micro-monitors and assigned them to three conditions: the *Information* treatment, the *Information + Personalised Emission Profile* treatment, and the control group. The *Information* treatment consisted of weekly leaflets containing generic health-framed information on the risks related to indoor air pollution and multiple combustion activities, with special attention to wood burning. This treatment is expected to change households' behavior by highlighting the health risks associated with combustion activities. The information was provided on a weekly basis during ten weeks to ensure assimilation and salience (Loewenstein, 1996), and formatted in a way that facilitates a simple understanding and management of indoor polluting sources (Van Raaij and Verhallen, 1983). An example of the *Information* treatment is shown in Figure 2.A1 of the appendix. In contrast, households in the *Information + Personalised Emission Profile* treatment were sent the same generic information plus a weekly Personalised Emission Profile of their indoor pollution levels, consisting of the graph of precise meter readings of the concentration of PM2.5 measured every five minutes over the

last week, as well as statistics to compare their emissions to the emissions of similar households (in fact, the control group). An example of the Personalised Emission Profile is shown in Figure 2.A2 of the appendix. Receiving real-time feedback in the form of a weekly Personalised Emission Profile is expected to reinforce the effect of generic information by activating complementary behavioural levers: first, it makes the hazards of wood burning more visible and allows for a better understanding of the relationship between specific activities undertaken over the last week and subsequent PM2.5 emissions, which reduce inattention and imperfect information biases. Second, building on prior research showing that social norms are an efficient lever of behavioural change (Allcott, 2011; Goldstein, Cialdini and Griskevicius, 2008; Ferraro and Price, 2013; Stok et al., 2016), the Personalised Emission Profile activates social comparisons by providing participants with their rank compared to the other households included in the study. Social comparison addresses biased beliefs about one's own consumption behavior in comparison to others. For example, a person might underestimate her actual pollutant emissions when compared to other households. This biased belief can be corrected by a social comparison. Accordingly, social norms can constitute a reference point from which deviation typically leads to dis-utility caused by social disapproval. Social comparisons may also evoke feelings of competition. Both treatments were implemented during ten weeks from January the 6th to March the 9th, 2020. To evaluate the impact of these treatments, we use high-frequency data on households' PM2.5 emissions over almost four months (four weeks before the interventions, ten weeks during the interventions, and two weeks after the interventions).

We find that the *Information + Personalised Emission Profile* treatment was successful at decreasing indoor levels of PM2.5 by more than 20% over the four-month period, with a sustained and significant decrease starting on the 3rd week after the beginning of the intervention. Heterogeneous impact analysis reveals that

the effect is concentrated in the most polluted households who exhibit a 40% decrease in PM2.5 concentration levels. For that group, the number of days over the WHO 24-hr limit -not to be exceeded more than 3 days per year- decreased by 52%, from 12.4 down to 5.9 days over the study period. This result is in line with the notion that the *Information + Personalised Emission Profile* treatment helps eliminate "slack" in combustion activities. In contrast, we observed no change in indoor air quality for households receiving the *Information* treatment, suggesting that generic information about the health risks of combustion activities is not sufficient to induce behavioral changes.

Turning to mechanisms, we find that both interventions were successful at increasing the perceived detrimental impact of wood burning and smoking on indoor and outdoor air pollution, and at decreasing declared frequency of wood burning in the future. We find no evidence of an impact on pollution health risk perception, attitudes toward wood burning regulation, pleasure when lighting a fire, nor on the intention to change wood burning equipment in the future. Declared frequency of combustion activities was not different between the control group and both treatment groups, as well as air quality improving activity, which is at odds with the objective reduction in PM2.5 concentration observed by micro-monitors. Our interpretation is that self-reported combustion and air quality improving activities are not accurate and precise enough to capture the behavioral changes that happened in the households. Interestingly, both generic and personalised information were efficient at improving knowledge on risks associated with combustion activities, but only personalised information was able to also induce behavioral changes. This finding indicates that pure knowledge and awareness is not sufficient to change behavior, and that the combination of real-time feedback and social comparison is a powerful lever to overcome remaining obstacles such as inattention and biased belief about one's own emission profile.

Our paper makes several contributions to the literature. First, it adds to the limited evidence on the use of smart meters to change behaviors. The originality of smart meters is that they provide real-time, accurate, high-frequency data on one's energy consumption or emission profile, which may be an effective way to overcome inattention and imperfect information bias by making the implications of one's behavior salient in real time. However, rigorous evidence on the actual effectiveness of smart meters in changing behaviors is scarce. Buchanan, Russo and Anderson (2015) deplore that the UK government requires energy suppliers to install smart meters in every domestic property as a way to allow consumers to monitor both their electricity and gas consumption despite the lack of quantitative evidence on the contribution of meter readings to energy conservation. Since then, two sets of trials have been published showing positive effects of smart meters on behaviors. First, Tiefenbeck et al. (2018) and Tiefenbeck et al. (2019) show that providing people with real-time water consumption profiles while showering reduces water consumption by 11% in hotel rooms and by 22% at home. Second, Hovell et al. (2020) and Hughes et al. (2018) show that immediate light and sound alerts from air particle monitors when concentration gets above a threshold reduces indoor smoking and particle events. Our paper innovates by providing first experimental evidence on the effectiveness of air quality micro-monitor technology in reducing PM2.5 emissions.[2] It adds to the nascent literature showing how digitalization in our everyday lives makes information available that can help individuals improve their behavior.

Second, our paper contributes to the literature on the effectiveness of information provision in shifting behavior. A number of studies have shown that information provision can effectively lead to the adoption of desired behaviours (Jensen, 2010; Dupas, Huillery and Seban, 2018; Allcott, 2011). However, meta-analyses generally

[2]Some studies suggest that micro-monitors detecting ambient PM2.5 may help change behavior but these studies do not use rigorous experimental methods (Klepeis et al., 2013; Wong-Parodi, Dias and Taylor, 2018; Heydon and Chakraborty, 2020; Iribagiza et al., 2020).

find great heterogeneity in the effectiveness of information provision (Andor and Fels, 2018*b*; Karlin, Zinger and Ford, 2015), suggesting that the content and format of the information matter a lot for its effectiveness. For example, Ek and Söderholm (2010) shows that information presented in a more concrete and specific way is more likely to affect behavior than more general information. Dupas (2011) showed that an HIV education campaign in Kenya led by school staff was ineffective in changing behavior, whereas it did improve behavior when animated by an external consultant conveying more realistic advice. The key question for policymakers is thus what information is most effective in changing behavior. In this paper, we make an important contribution to this question by comparing the effectiveness of generic *versus* personalised information. In a review of thirty-eight interventions to encourage energy conservation, Abrahamse et al. (2005) conclude that generic information alone tends to result in higher knowledge levels but not necessarily in behavioral changes. However, more recent experimental papers have shown that generic information alone can be effective in changing behavior (Dupas, 2011; Dupas, Huillery and Seban, 2018; Jensen, 2010; Hine et al., 2011). Other papers show that personalised information can also be effective, be it social comparisons (Allcott, 2011; Allcott and Rogers, 2014; Ayres, Raseman and Shih, 2013) or tailored feedback and advice (Karlin, Zinger and Ford, 2015; Abrahamse et al., 2007*a*; Madajewicz et al., 2007; Jalan and Somanathan, 2008). But very few studies compare one against the other, and both against no information, as we do in this paper. Notable exceptions are Ferraro, Miranda and Price (2011) and Ferraro and Price (2013) who show that technical advice on water conservation had no impact on household conservation behaviour unless messages were augmented to include pro-social messages and social comparisons, the latter being the most efficient piece of information with lasting effects. Goldstein, Cialdini and Griskevicius (2008) compares the effectiveness of social norm *versus* environmental protection messages in encouraging towel re-use

in hotels, and find that social norms messages induce larger behavioral responses. Finally, De Vries et al. (2008) and Celis-Morales et al. (2017) show that receiving personalised feedback and advice on diet and physical activities improves health relative to generic information. Our paper adds to this literature by testing two different information contents against a control group and comparing their relative effectiveness. We show that generic information is not enough to shift behaviour; although both the *Information* and *Information + Personalised Emission Profile* groups received similar information on indoor pollution sources and its detrimental impact on health risks, only households receiving personalised air quality meter readings changed their behaviour and decreased their indoor pollution. This result further enriches the literature on the awareness–behaviour gap, whereby individuals are aware of an issue, like climate change, air pollution, or the importance of preventive behaviors, but fail to undertake concrete actions (Gifford, Kormos and McIntyre, 2011; Kennedy et al., 2004; Schwarzer, 2008). Our paper shows that this gap can be reduced by providing individuals with accurate real-time information on their emission profile and social comparisons. These results may be of particular interest for policymakers in a context where micro-sensor technologies that detect ambient PM2.5 levels are increasingly available and affordable (Jiang et al., 2011).

One limitation of our paper relates to its external validity. We focus on households voluntary to participate in the study and using wood burning as a complementary but not only heating source. Consequently, our sample is probably more interested in air pollution than the average, and we also observe that it is more educated and wealthier than the national average, and exhibit lower levels of indoor air pollution. This may affect treatment effects both upwards or downwards—the theoretical predictions going in both directions. This paper can thus pave the way for replications on more representative samples.

The paper is organized as follows. Section 2.2 describes the context on air quality

and wood burning in Île-de-France and details the intervention and experimental design. Section 2.3 presents our data, outcomes of interest and sample. Section 2.4 examines the validity of the experiment and presents the estimation method. Section 2.5 provides the results on indoor air quality, and section 2.6 on knowledge, attitudes and self-reported behaviour. Section 2.7 concludes.

2.2 Context and experimental design

Air quality and wood burning in Île-de-France

Knowledge and perceptions on indoor air quality Despite being an important health hazard in France, there is limited awareness of indoor air pollution, its sources and its health impacts. The Indoor Air Quality Observatory estimated that 34% of French dwellings register unsafe levels of PM2.5 (OQAI, 2005) and an estimated cost of €19 billion per year is attributed to indoor air pollution alone, including €1 billion in asthma medication reimbursement costs for example (Boulanger et al., 2017). Yet, while almost 90% of residents in the Île-de-France region[3] believe that outdoor air pollution presents a major health risk, less than 50% believe so about indoor air pollution (Menard et al., 2008) and overestimate indoor air quality (Langer et al., 2017). In fact, households still show limited understanding of the different sources of indoor pollution and underestimate its associated sanitary risks (Grange, Sommen and Host, 2012; Daniel et al., 2020). For example, although burning incense and candles can release up to 10 times more PM2.5 than a cigarette, 68% of candle users and 58% of incense users stated that this practice has no effect on or even improves indoor air quality (Nicolas et al., 2017; Tirler and Settimo, 2015; Stabile, Fuoco and

[3]Île-de-France (Paris and its suburbs) is the most populous of the eighteen regions of France and is centred around the capital Paris, in the north-central part of the country. It includes eight administrative departments: Paris, Essonne, Hauts-de-Seine, Seine-Saint-Denis, Seine-et-Marne, Val-de-Marne, Val-d'Oise and Yvelines.

Buonanno, 2012; Andersen et al., 2006).

Wood burning: use and perceptions Wood burning is another major source of PM2.5 both inside users' homes and in the region's ambient air, but a large fraction of this pollution is avoidable. A 2014 report by the Agency for the Environment and Energy Management (ADEME) estimates that 16% of households in the Île-de-France region, which amounts to about 79,8000 households, declare owning a wood burning equipment. But contrary to users in low- or middle-income countries that rely on wood combustion for heating and cooking (Gordon et al., 2014), the vast majority of them (83%) use wood burning as an auxiliary or occasional heating source. Besides, most users have not invested in efficient wood burning equipment and have insufficient knowledge of good wood burning practices (ADEME, 2015), which would lead to high levels of indoor pollutant exposure (Chafe et al., 2015). Given that the region is densely populated, occasional wood burning using old equipment by a minority of households generates a great amount of outdoor pollution and is responsible for more than one third of fine particle emissions in the region's ambient air during winter. Given its occasional use, a non-trivial number of users could limit or eliminate the use of wood burning with little to no adjustment to their budgets.

However, little awareness of the negative health impacts of wood burning results in low effectiveness and acceptability of environmental policy measures. On the contrary, wood burning is seen as a low cost and green heating source. For instance, a €1,000 subsidy was introduced by the regional authorities in 2018 to replace old equipment by less polluting ones, but the take-up was only 2%. This is not surprising considering that only 21% of occasional users believe that wood burning has an impact on indoor air quality, a proportion that drops to 16% when it comes to outdoor air quality. Regarding prohibition policies, 48% of users also said they would not respect a ban (BVA/ADEME, 2014). In fact, a ban on wood burning by the City of Paris in 2014

was faced with intense public and political backlash, leading to a lift of the ban by the Minister of the Environment[4].

Merely informing users about the dangers of wood burning may thus be an effective strategy in this context. On the other hand, the strong positive feeling associated with wood burning may weaken the effectiveness of informational campaigns. The ADEME 2014 report shows that, when presented with facts about the outdoor pollution attributed to wood burning, 30% of occasional wood burning households do not believe the figures (BVA/ADEME, 2014). Behavioural interventions may thus be required on top of generic information at reducing wood burning.

The interventions

The goal of the proposed interventions is to examine the effectiveness of air quality information in limiting household polluting activities and enhancing indoor air quality. The interventions were developed by researchers in economics and psychology, in collaboration with the Inter-ministerial Directorate for Public Transformation (DITP) and the Île-de-France Regional and Intergovernmental Department of Environment and Energy (DRIEE). Both interventions involved mailing eight leaflets[5][6] between January and March 2020. All households participating in the study were equipped with air quality monitors. In order to discern the impact of personalised feedback from generic information provision, we distinguish two treatments.

The *Information* Treatment In the *Information* treatment, we sent households informational leaflets on different PM2.5 emitting activities, their associated health risks, as well as tips to improve indoor air quality. Each leaflet was composed of a cover

[4]Laetitia Van Eeckhout. "Pourquoi Ségolène Royal veut revenir sur l'interdiction des feux de cheminée en Île-de-France. *Le Monde*. December 2014. https://www.lemonde.fr/planete/article/2014/12/09/segolene-royale-veut-revenir-sur-l-interdiction-des-feux-de-cheminees_4536996_3244.html

[5]The first two leaflets were sent two weeks apart, while the following six were sent every week.

[6]All materials can be found in the online appendix: https://osf.io/5br8y/

page containing an illustration and a catchy slogan, a page containing infographics on sources of indoor air pollution and health risks, and a page detailing good practices. The focus, the cover, and the messages were different is each wave. We put an emphasis on wood burning in the last five waves of the intervention (weeks 4 to 8) to overcome households' low awareness of the negative effects of wood burning. The positive image of wood burning was challenged by matching the pollution produced by wood burning to that of other sources that are already perceived as detrimental, such as cigarettes and car exhausts. Framing the impact of wood burning as a direct threat to users, by focusing on indoor rather than outdoor air pollution, is inspired by a large body of research demonstrating that communication of environmental issues is more successful at changing behaviour when presented in a public health frame rather than an environmental or monetary cost frame (Pelletier and Sharp, 2008; Asensio and Delmas, 2016; Cardwell and Elliott, 2013; Myers et al., 2012).

The *Information + Personalised Emission Profile* Treatment The second treatment provided households with the same generic information as in the *Information* Treatment, but added people's personalised emission profile based on their real PM2.5 emissions over the last week. Using data from the air quality monitors, the households' indoor PM2.5 concentration was measured every 5 minutes and represented on a figure along with the date and hour of the major pollution peaks. The Personalised Emission Profile also included a ranking of the household in terms of air quality compared to households in the control group. The Personalised Emission Profile can alter household polluting behaviour through four different channels. First, the graphs help households identify pollution peaks that occurred in the past seven days and encourage them to link these peaks to domestic activities, which provides a better understanding and management of indoor air quality. Second, as pollutants are invisible to the human eye (Gee et al., 2013) and their costs on health are often

in the long run, the graphs can help households overcome salience and discounting bias by making the intangible aspect of pollution visible in the present. Third, the personalised statements could reinforce the overall credibility of the generic information. Finally, the use of social comparison may stimulate behavioural change.

Experimental design

To measure the differential effect of the two treatments, 281 households received a micro air quality monitor and were asked to plug it in their living room. Using a baseline questionnaire, households were stratified by the presence of a smoker in the household and then matched into the best triplets according to their average weekly PM2.5 levels at baseline[7]. This resulted in 94 triplets. Within each triplet, households were randomly assigned to one of 3 groups; 94 households received the *Information* treatment, 94 households received the *Information + Personalised Emission Profile* treatment, and 94 households received no leaflets and served as the control group. At the end of the intervention, the control households were given access to the informational campaign, and both the *Information* and control groups received their indoor air quality Personalised Emission Profile for the entire intervention period.

2.3 Data and Sampling

Data sources and outcomes of interest

Micro-monitor indoor pollution data

All households in our sample were equipped with a micro-monitor that retrieved PM2.5, PM10, temperature and humidity levels every five minutes and transmitted it to an online platform set up by the manufacturer, using the 2G Network. Participating

[7] Both smoking and baseline indoor PM2.5 levels highly predict indoor air pollution post-treatment

households were asked to position the monitor no closer than 1m and no farther than 4m away from their wood burning equipment. In order to minimise the experimenter demand effect, the chosen micro-monitors[8] are discrete, small (a square of 12cm), and have no direct/visible indications about the measured air quality.

The micro-monitor thus had two functions; it served as one intervention instrument, allowing to send personalised summaries on air quality to households in the *Information + Personalised Emission Profile* group, as well as a reliable way to measure the impact of the two treatments given that the difference in the levels of indoor pollution between each treatment group and the control group is the most consistent and reliable indicator of change in household behaviour.

Following our main pre-registered hypothesis, we expect that the intervention would have an impact on household's PM2.5 emission profiles. The micro-monitor indoor pollution data allows us to measure the main outcome of interest to test this hypothesis, namely households' average daily PM2.5 level over the whole post-treatment period. Another outcome of interest is the number of days a household registered higher PM2.5 levels than the WHO 24hrs guidelines (over 25 µg/m^3).

Self-reported questionnaire data

Households completed one online questionnaire at baseline and one at endline. Baseline data were collected from August through December 2019 and were used to identify households who use wood burning. The endline questionnaire was administered at the end of March 2020, 3 weeks after the end of the intervention. The endline questionnaire measured three types of outcomes to look at the mechanisms of change in indoor air quality between the three groups.

Perception and knowledge about air pollution The baseline and endline questionnaires included questions about the household's perceived indoor and outdoor

[8] Atmotrack Atm01 by 42 Factory: https://atmotrack.fr/

air quality, knowledge of main indoor and outdoor sources of pollution, and perceived impact of air pollution on health.

Perception, knowledge and attitude about wood burning The baseline and endline questionnaires included a set of variables reflecting the household's perception on the contribution of wood burning to indoor pollution, knowledge of good wood burning practices, attitude towards wood burning regulation, the pleasure when lighting a fire, as well as the intention to change wood burning equipment in the future.

Self-reported polluting activities We collected information about households' self-reported polluting activities, such as the frequency of wood burning over past winter, its intended use in the future, and the number of times they engaged into smoking, wood burning, candles, incense, and dusting over the past week.

The baseline questionnaire also collected information about the household's socioeconomic and demographic characteristics (age and educational level of the respondent, monthly household income, number of residents), self-reported health status (subjective health status, the presence of a person with respiratory problems in the household, investment in health, the presence of a smoker in the household), environmental beliefs and attitudes, and type of wood burning equipment. See online appendix for a full list of baseline and endline questions.

Sampling strategy and sample characteristics

The experiment was presented on a website where applicants could volunteer to install an air quality micro-monitor in their homes for six months and receive information on ways to decrease indoor pollution. Participants who wished to be part of the study were asked to fill out a recruitment survey (which also served as the baseline questionnaire) in which they specified their heating methods and frequency,

and a set of household characteristics. The call for volunteers was advertised through multiple channels : first, the Regional and Intergovernmental Department of the Environment and Energy (DRIEE) passed on our call for volunteers to local communities, authorities, and institutions. Second, we emailed a list of households identified as wood burning households by the Agency for the Environment and Energy Management (ADEME). Finally, we relied on a collaborative network of brands and consumers, "Wedoolink". A total of 4,200 people volunteered to take part in the study. Within this sample, 558 people used wood burning, of whom 370 reported using wood burning as an occasional heating method. Only these households were included in the study, whereas those using wood burning as their only source of heating were excluded. We choose to restrict the study sample households that burn wood occasionally for two main reasons: firstly, when a household's main heating source is wood burning, a change in behaviour is constrained by more barriers such as financial or mechanical, resulting from installation of other heating alternatives. The aim is to limit *avoidable* burning of wood. Due to technical issues related to the strength of the 2G signal, 36 households could not be included because their micro-monitor did not transmit data consistently. We also asked participants to tell us whether they knew people taking part in the study and identified 13 clusters of "friends". In order to avoid spillovers, one individual in each cluster was randomly included in the study. The final sample included 281 households, mostly residents of the Ile-de-France region.

Column 1 in Table 2.1 presents the characteristics of the households at baseline. The sample is not representative of the French population, but it is comparable to the population of occasional users of wood burning in the Île-de-France region (BVA / ADEME, 2015). Respondents have a mean age of 49 years, they are highly educated (46% have a Masters degree or more), and they are of middle-high to high income status (80% earn more than €3400 per month). In the sample, air quality at home

is wrongly perceived as being better than air quality in the neighbourhood, which is itself perceived as better than the air quality of the entire Île-de-France region. Regarding wood burning, 55% of respondents believe it to be an important source of outdoor pollution, and 36% list it as an important source of indoor pollution. Half of the households use wood burning more than once a week, 32% use it more than once a month, and 17% use it once a month or less. The baseline picture thus shows large margins of improvement in households' knowledge and behavior.

2.4 Validity of the experiment and estimation method

Validity of the experiment

Balance checks Table 2.1 presents balance tests of household characteristics across treatment arms. We observe some imbalances in the Environmental Attitudes score and respiratory problems in the household between the *Information* treatment and control groups, the perception of air quality in the region between both treatment groups and the control group, and the type of equipment between the *Information* treatment and control groups as well as between the *Information* and the *Information + Personalised Emission Profile* treatment groups. We find eight significant differences in means out of a total of 81 tests, which is exactly what we expect under the hypothesis that all groups are drawn from identical underlying distributions and that differences are pure chance due to sampling fluctuations. The balance checks thus do not reject the assumption that each treatment group is statistically identical to the control group. We ran the analyses both including and excluding these variables as controls and found qualitatively and quantitatively similar estimates across specifications, which suggests that the bias introduced by

these baseline differences does not account for our results.

Attrition There was no attrition for indoor air quality monitor data. Attrition was very small at endline (4.6%) and was evenly distributed across the three groups[9].

Estimation method

Indoor air quality

We measure the Average Treatment Effects of both interventions on indoor air quality by running the following regression:

$$Y_{i,j,post} = \alpha + \beta T_{1,i} + \gamma T_{2,i} + \theta_j + \epsilon_{i,j} \tag{2.1}$$

where $Y_{i,j,post}$ represents the outcomes of interest for household i in triplet j, $T_{1,i}$ is a dummy indicating that the household is in the *Information* group, $T_{2,i}$ is a dummy indicating that the household is in the *Information + Personalised Emission Profile* group, θ_j is a vector of triplet fixed effects aimed at reducing the variance of the treatment effect estimators (Abadie et al., 2017), and $\epsilon_{i,j}$ is the heteroscedasticity robust error term.

To exploit longitudinal variations in indoor PM2.5 levels, we estimate how the treatment effect varies over the 3-month intervention period. The permanency of behavioural changes following information campaigns is often questioned, as the effect is expected to be concentrated in the "hot phase" of decision making, the first weeks following the beginning of the intervention, but might then decay as the novelty effect dissipates (Allcott and Rogers, 2014; Ferraro and Price, 2013; Gneezy and List, 2006). In contrast, the intervention could alter beliefs and attitudes and lead to long-lasting behavioural changes. To capture the short-run dynamics of the effect, we interact

[9] A linear probability model regression fails to reject the null hypothesis that the probability of having baseline data is similar between the three groups. Results are shown in the Appendix Table 2.A1

both treatment variables $T_{1,i}$ and $T_{2,i}$ with a set of weekly indicator variables W_k, with k denoting the week since the start of the intervention:

$$Y_{i,j,k} = \alpha + \sum_{k=-2}^{11} \beta_k T_{1,i} W_k + \sum_{k=-2}^{11} \gamma_k T_{2,i} W_k + \sum_{k=-2}^{11} W_k + \theta_j + \epsilon_{i,j,k} \tag{2.2}$$

$\epsilon_{i,j,k}$ is clustered at the household level and at the week level, and robust to heteroscedasticity. β_k thus provides the impact of *Information* treatment in week k, while γ_k provides the impact of *Information + Personalised Emission Profile* in week k.

Heterogenous treatment effects

As intended in the pre-analysis plan, we test whether treatment effects are different depending on the initial level of PM2.5 emission. On the one hand, people with a high baseline level of PM2.5 emission may be more likely to respond to the interventions as there is more room for change. On the other hand, their high emission profile may reflect constraints that render their beliefs and behavior more persistent (e.g., less education, less economic affluence, or lower level of trust). Theoretically, how the initial level of PM2.5 emission affects treatment effects is thus ambiguous. To test it, we add dummy variables indicating the quartile of baseline PM2.5 level, as well as the interaction between each of these dummies and the treatment variables.

We also hypothesised that the impact might vary as a function of outdoor temperatures. While on very cold days, a household has to use wood burning for complementary heating, on warmer days the use of wood burning is more likely to be for recreational purposes, leading to a larger margin of improvement. To that end, we use household daily outdoor temperature and interact the treatment variables with three temperature categories: cold days (<8 degree C), moderate days (between 8 and 14 degrees) and warm days (more than 14 degrees). Outside local temperature levels were retrieved from "Météo France", the official public administrative institution of

meteorology and climatology in France. The daily temperature was assigned to each household based on the closest meteorological station available.

Mechanisms

To measure the treatment effects on outcomes measured in the endline questionnaire, we use an OLS regression without including triplet fixed effect in order to avoid a loss of observations and statistical power due to attrition in the endline questionnaire:

$$Y_{i,post} = \alpha' + \beta' T_{1,i} + \gamma' T_{2,i} + \epsilon'_i \tag{2.3}$$

2.5 Impacts on indoor air quality

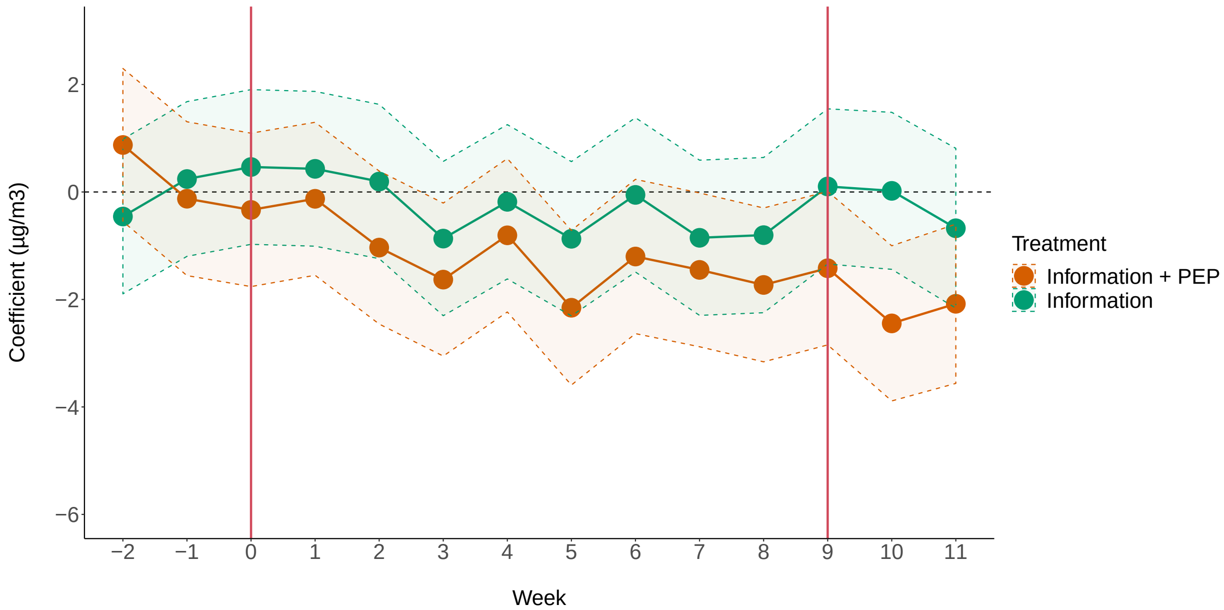
Average treatment effect

Table 2.2 presents the impact of the interventions on indoor air quality. Column (1) shows the ATE estimates on average daily PM2.5 level over the whole post-treatment period using the main specification (equation 2.1). While the *Information* treatment led to no significant change in average indoor air quality in treated households, the *Information + Personalised Emission Profile* treatment induced a 1.315 µg/m^3 decrease in average daily PM2.5 over the post-treatment period, representing a 24% decrease relative to the control group mean. This is robust to the inclusion of controls to correct for baseline imbalances (Column 2).

Figure 2.1 provides insights on the dynamics of the impact across time: it displays the ATE estimates interacted with dummies indicating the weeks since the first message, after adjustment for triplet and week fixed effects (equation 2.2). While the households receiving the *Information* treatment show no difference in indoor air quality compared to the control group in any week throughout the whole intervention period, the *Information + Personalised Emission Profile* intervention started to

have an impact on polluting behaviour rather fast: the effect is significant starting the third week after the start of the intervention and is persistent throughout weeks 5, 6 and 8 of the intervention, and weeks 10 and 11 after the end of the intervention. There is no noticeable decay of the effect throughout the 3 months of treatment—if anything rather an amplification, indicating that there was no habituation effect to the novelty of the messages or to the monitor.

Figure 2.1: Average treatment effects on Indoor daily PM2.5 levels, by week since the first message



Notes: Confidence intervals are computed at the 95% confidence level. The figure represents the coefficients on the interaction between each intervention dummy and weekly dummies. Triplet and weekly fixed effects are included. Standard errors are clustered at the household and week levels. The two solid vertical lines represent the start and the end of the intervention. Week 0 starts on January 6th 2020, when the first message was sent the participants in the *Information* and *Information + Personalised Emission Profile*. The last message was sent on the 9th of March 2020, on week 9.

Heterogeneous effects

In this section, we test whether the effectiveness of the intervention depends on the household's initial level of pollution and on outside temperature.

Initial level of pollution In line with other personalised feedback and social comparison interventions (Allcott, 2011; Ferraro and Price, 2013; Schultz et al., 2007*a*), the households that are more polluted to begin with respond more to the *Information + Personalised Emission Profile* intervention. Table 2.3 shows the treatment effect by quartile of baseline PM2.5 concentration. The treatment effect of the *Information + Personalised Emission Profile* intervention is concentrated in households in the 4th quartile of baseline PM2.5 concentration, i.e. the highest polluters. In that group, the *Information + Personalised Emission Profile* intervention decreased indoor PM2.5 levels by 4.9 µg/m^3, a 36% decrease compared to the control group mean, significant at the 95% confidence level. These households are less affluent, reported the presence of a smoker and using wood burning equipment more frequently and declared a better subjective health status (a comparison of the baseline characteristics of households in the 4th quartile as opposed to other quartiles of baseline pollution can be found in Appendix Table 2.A2). Households in the third quartile receiving the *Information* treatment decrease their indoor pollution by 18% (-0.78µg/m^3). This decrease is only significant at the 10% level and is much smaller in absolute size. While the effect is not significantly different than 0 in the households with the best indoor air quality, the boomerang effect found in other normative feedback experiments, which leads households that are better than average to pollute more, is not found here (Ayres, Raseman and Shih, 2013; Schultz et al., 2007*a*).

Figure 2.2 shows the dynamics of the treatment effect (equation 2.2) by quartile of baseline indoor pollution level. Regarding households exposed to the *Information* treatment, there is no significant difference relative to the control group for any quartile of baseline level of pollution. In contrast, regarding households exposed to the *Information + Personalised Emission Profile* intervention, the treatment effect is significant for the highest quartile of baseline indoor pollution every week starting

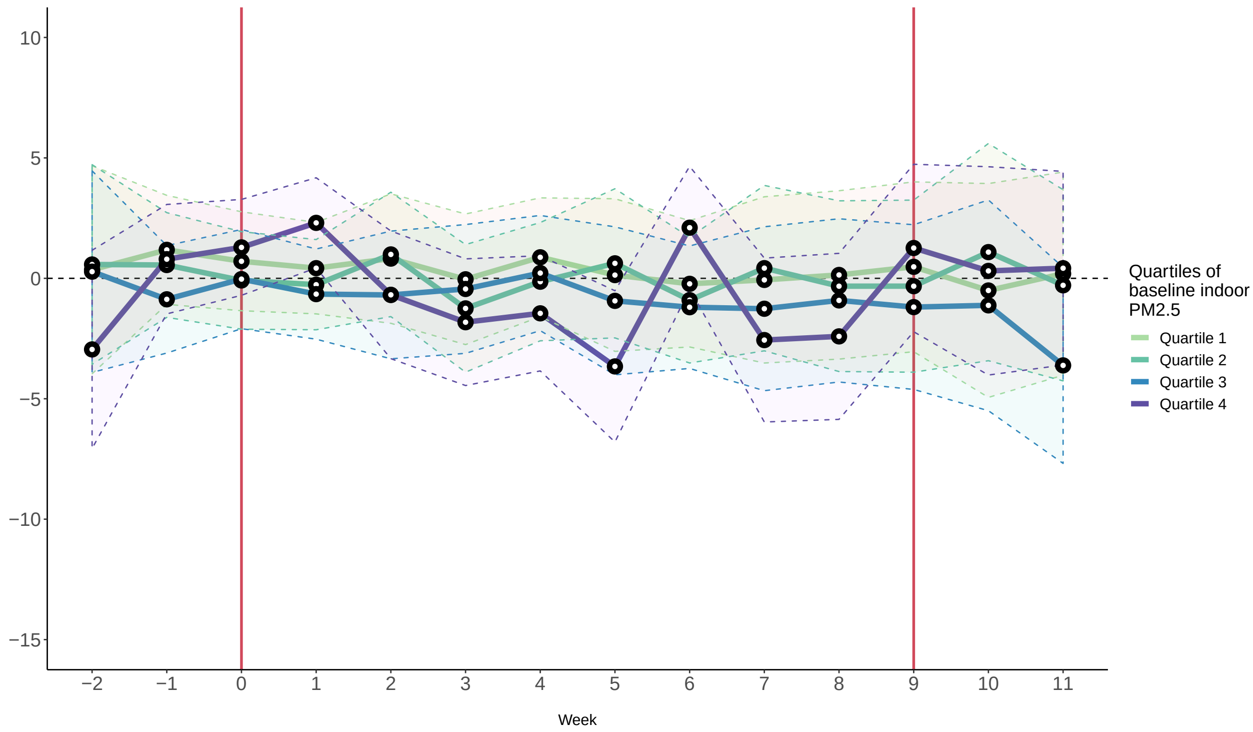
the second week after the reception of the first leaflet.

Outside temperature levels Table 2.4 shows the estimates of the treatment effect on daily levels of indoor PM2.5, on three different sub-samples: days where the household's municipality recorded outside an outside temperature lower than 8°C (cold days), between 8 and 14°C (moderate days) or above 14°C (warm days). While we see a significant treatment effect of the *Information + Personalised Emission Profile* intervention on cold and moderate days, with a bigger and more significant effect on moderate days (-1.3 µg/m^3, p<0.01) , the treatment effect is not significant on warmer days. We keep in mind, however, that we encounter far fewer days with a temperature above 14°C leading to lower statistical power. However, the differences in ATE between cold, moderate and warm days are not statistically significant (see p-values at the bottom of Table 2.4).

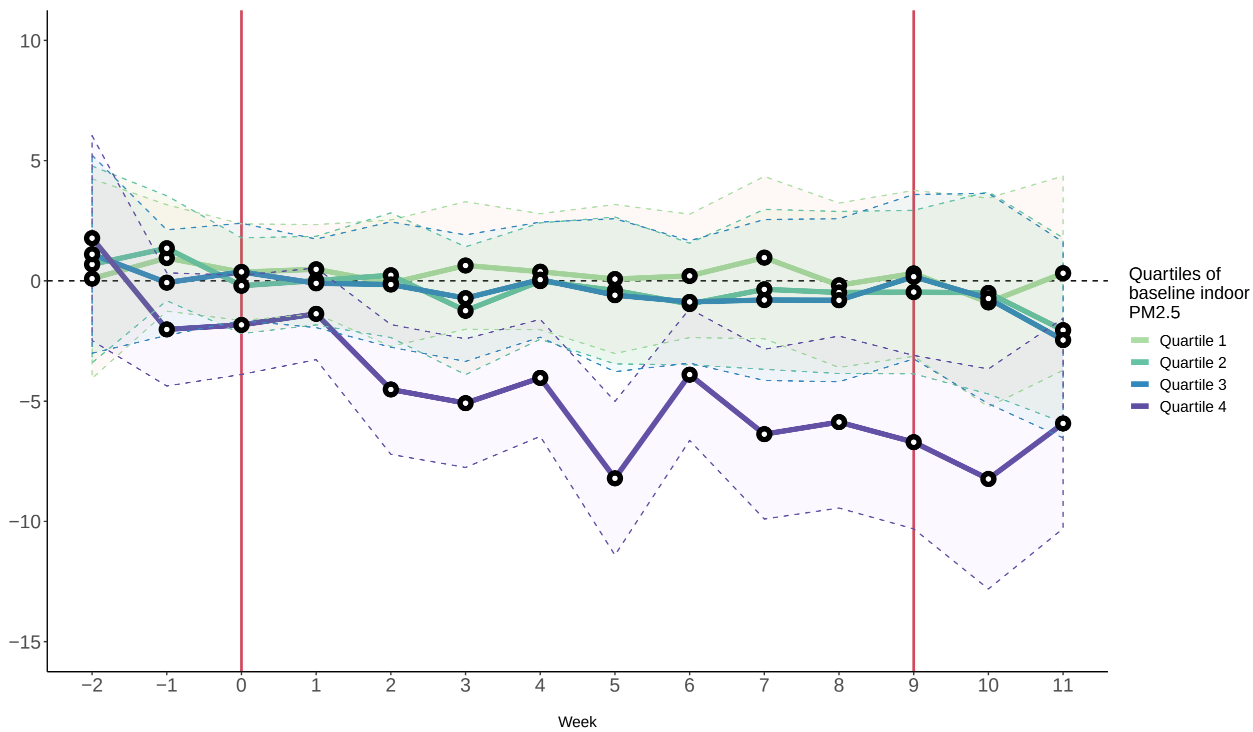
Number of days over the WHO 24-hour guideline

Another outcome of interest is the number of days a household was exposed to extremely dangerous levels of pollutants. The WHO guidelines on PM2.5 24-hour exposure is 25 µg/m^3 not to be exceeded more than 3 days a year. Table 2.5 reports the average treatment effect of the interventions on the number of days exceeding this threshold over the study period, i.e., 77 days. Note that in the control group, the average number of days above the threshold is 2.9 days over only four months, thus well above the WHO recommendation. We see no impact of the *Information* treatment, which confirms that this intervention was not sufficient to induce a change in behavior. In contrast, the *Information + Personalised Emission Profile* treatment reduced the number of days exceeding the WHO threshold by 1.44 days, a 50% decrease compared to the control group mean, significant at the 10% level (Table 2.5, Column 1). The effect is greatly heterogeneous as it concentrates only on the

Figure 2.2: Average treatment effect on Indoor PM2.5 levels, by week and quartile of baseline PM2.5



(a) *Information* treatment



(b) *Information + Personalised Emission Profile* treatment

Notes: Confidence intervals are computed at the 95% confidence level. The figure represents the coefficients on the interaction between each intervention dummy and weekly dummies. Triplet and weekly fixed effects are included. Standard errors are clustered at the household and week levels. The two solid vertical lines represent the start and the end of the intervention. Week 0 starts on January 6th 2020, when the first message was sent the participants in the *Information* and *Information + Personalised Emission Profile*. The last message was sent on the 9th of March 2020, on week 9.

most polluted households (4th quartile of baseline PM2.5 concentration): for these households, the *Information + Personalised Emission Profile* treatment induced a decrease of days above the WHO threshold from 12.4 days down to 5.9 days over a period of four months, a change significant at the 5% level (Table 2.5, Column 5). For the other less polluted households, the number of days above the WHO threshold is already very small and in line with WHO recommendation (0.12-0.57 days over four months on average), and we see no impact of the treatments. It is fortunate that the households who respond to and benefit from the intervention are those who actually need it.

Magnitude of the effects and sanitary impacts

The magnitude of the effect of the *Information + Personalised Emission Profile* intervention is sizeable, considering that the effect sizes of similar interventions aimed at energy conservation typically vary between 2% and 20% (Karlin, Zinger and Ford, 2015). From a public health perspective, a decrease of 1.315 µg/m^3 in average exposure to PM2.5 is non-negligible. In fact, studies have shown that an increase in exposure of as little as 1 µg/m^3 can have serious health consequences. For instance, an increase of 1 µg/m^3 in PM2.5 was associated with a dementia incidence of a 1.55 hazard ratio (Oudin et al., 2018) and an 11% increase in COVID-19 mortality rates (Wu et al., 2020). A review on Medicare patients in the U.S. showed that an increase in short-term exposure to PM2.5 of 1 µg/m^3 is associated with an annual increase of 3,642 hospital admissions, 20,000 extra hospitalisation days and almost $70m in care cost at the country level (Wei et al., 2019). The sanitary impacts are even more important for the most polluted households where the *Information + Personalised Emission Profile* intervention led to a decrease in average daily PM2.5 levels of 4.9 µg/m^3. In fact, it was found that an improvement in PM2.5 exposure of 5 µg/m^3 is associated with a 16% decreased incidence of hypertension and the total annual

economic benefits of decrease of ambient air pollution by 5 µg/m^3 in Paris is estimated to be around €3.6 billion, including reductions in health spending, productivity loss and immaterial costs namely quality of life and life-expectancy (Pascal et al., 2013).

2.6 Mechanisms

Knowledge about indoor PM2.5 sources

The interventions provided information on the different sources of PM2.5. Table 2.6 displays the treatments' impact on the probability of correctly citing different indoor PM2.5 emitting sources. Both interventions lead to an important increase in the probability of reporting wood burning and cigarette smoking as a main source of indoor PM2.5; households that received the *Information + Personalised Emission Profile* were 50% and 136% more likely to cite wood burning and cigarette smoking compared to the control group. The *Information* treatment lead to a similar increase in magnitude in the reporting of wood burning as a main source of PM2.5, and an increase of 100% when it comes to cigarettes, though only significant at the 10% level. Conversely, Neither the *Information* nor the *Information + Personalised Emission Profile* increased the probability of citing candles, incense and cooking as major indoor PM2.5 sources.

Beliefs, knowledge, and attitude about wood burning pollution

The interventions provided information on the health and environmental risks of PM2.5 emissions with an important focus on wood burning. The top panel of Table 2.7 details the average treatment effects of both interventions on beliefs, knowledge, and attitudes towards wood burning, while the bottom four panels shows the treatment effect by quartile of baseline PM2.5. Neither the *Information* nor the *Information + Personalised Emission Profile* interventions had an impact on the health risk

perception of pollution (Column 1). In contrast, both interventions increased the perceived impact of wood burning on indoor air quality, by 6 points (on a score from 0 to 100) in the *Information* group (significant at the 10% level), and by 9 points in the *Information + Personalised Emission Profile* group (significant at the 1% level), off a base score of perceived risk of 60 in the control group. This effect was concentrated in the most polluted households (quartile 4), whose baseline perceived risk of wood burning was lower (the control group mean is 53 in quartile 4 *versus* 59, 65, and 61 in the other quartiles). and was almost twice as big (p-value=0.05) for the *Information + Personalised Emission Profile* treatment (20-point increase, significant at the 1% level) as for the *Information* treatment (12-point increase, significant at the 5% level). Providing the household with direct information on their own indoor PM2.5 profile thus reinforced the overall credibility of the generic messages more in households where pollution is high.

The belief that wood burning is a major source of outdoor pollution also increased in both treatment groups (Column 3): while 45% of households in the control group believe that wood burning is a major source of outdoor pollution, the intervention increases that proportion by 18.7 points in the *Information* group and by 14.3 points in the *Information + Personalised Emission Profile* group. In quartiles 1, 2 and 3 of baseline PM2.5 concentration, the effects are somewhat larger in the *Information* group than in the *Information + Personalised Emission Profile* group, whereas the opposite is true in the most polluted households (quartile 4). Estimates are quite imprecise though, and thus marginally significant and not always statistically different one from the other.

Another important component of the information leaflet provided to both groups consisted of information on how to decrease PM2.5 inside the household and the good practices to decrease emissions from wood burning. Column (4) in Table 2.7 presents the impact of the interventions on the probability of mentioning one good practice

in wood burning. While 67% of households in the control group name at least one good wood burning practice, this proportion increased by 13 percentage points in both treatment groups—significant at the 10% level. The effect seems larger in less polluted households (quartiles 1 and 2 of baseline PM2.5), which may be related to lower baseline knowledge of good practices, especially in quartile 2.

We did not observe significant impacts on households' attitude towards wood burning regulation, the pleasure felt when lighting a fire, or the intention to change wood burning equipment (Columns 5, 6, and 7). Overall, these results show that both interventions improved awareness of the role of wood burning in generating PM2.5 pollution and good practices to reduce pollution. These positive effects are not exclusive to a particular group of households but rather concern all of them, but some effects are particularly pronounced for most polluted households in the *Information + Personalised Emission Profile* group.

Self-reported polluting activities

Wood burning We asked households about the frequency of use of wood burning this past winter, and their intended frequency of use in the future. Table 2.8 shows the results of the declared frequency of use regressed on the two treatment dummies, controlling for baseline frequency. We observe no difference in the frequency of use of wood burning throughout the treatment period. However, both treated groups declared that they intend to decrease wood burning in the future. Compared to the control group, households exposed to *Information* or *Information + Personalised Emission Profile* are 12 percentage points less likely to declare that they intend to use wood burning "Once a week or less" next winter (a 25% increase from 48%, significant at the 1% level). This effect seems to concentrate in households in the second quartile of baseline indoor pollution. We also asked in the endline questionnaire "How many times in the last week have you used wood burning". The treatment effects on this

variable is shown in Column 1 of Table 2.9.

Other activity affecting air quality The declared frequency of other PM2.5 emitting activities does not differ significantly between the three groups. The households receiving weekly messages are not different from the control households in their declared frequency of use of electronic and tobacco cigarettes, candles, incense or dusting (Table 2.9). Similarly, we observe no significant change in the declared frequency of activities that improve indoor air quality (Table 2.10). Similarly, we observe no effect change on the extensive margin of polluting and air quality enhancing activity (Tables 2.11 and 2.12).

Interpretation Self-reported polluting activities are not affected by any intervention. This result is at odds with PM2.5 micro-monitor data showing a significant reduction in pollution in the *Information + Personalised Emission Profile* group. The discrepancy between objective PM2.5 measures and self-declared polluting activities may be due to the fact that households may not be able to report accurately their actions, may be because of memory issues or social desirability biases. Alternatively, our questions were not precise enough to capture the changes in behavior explaining the reduction in PM2.5 emissions. We observe that the self reported incidence of polluting and air quality improving activities does not predict levels of PM2.5 (Appendix Table 2.A3). These two interpretations point to the importance of collecting objective, non self-declared, measures in impact evaluations. A third interpretation may be that the decrease in indoor PM2.5 levels is not associated with a decrease in wood burning, a better management of firewood, nor a decrease in indoor smoking, incense, and candle, but to better ventilation and wood burning management. Although we observe that the frequency of ventilation has not changed between following the treatment, it is possible that treated households ventilate for a longer or at more appropriate times.

2.7 Conclusions

We conducted a randomized field experiment with occasional wood burning households in France to test the effectiveness of information provision and air quality monitors in decreasing indoor air pollution. We use the difference in the level of PM2.5 inside the home as an objective proxy of household polluting behaviour. Our results suggest that informational and personalised feedback on indoor air quality is effective at decreasing polluting activity and improving indoor air, particularly in the most polluted households at baseline. Personalised emission profiles could change household behaviour by providing salient direct information that help households update their beliefs and better manage their activity. The improvement in indoor air is noted starting the 3rd week after the beginning of the intervention, and shows no decay throughout the intervention period as well as two weeks after the end of the intervention. While the literature on feedback provision suggests that it is most effective when provided in high frequency/in real-time (Darby et al., 2006), our results show that weekly indirect feedback can still have an important impact on behaviour, in line with results from Allcott (2011) and Ehrhardt-Martinez et al. (2010).

Another main finding of our study is that while generic information on indoor air pollutants was effective at increasing households' awareness about the negative impacts of woodburning, it was only effective in changing polluting behaviour when augmented with personalised feedback on indoor air quality. This is also consistent with a large body of research documenting the awareness-action gap whereby greater knowledge about environmental and health issues does not necessarily result in preventive or pro-environmental behaviour (Kollmuss and Agyeman, 2002*a*; Rimal, 2000). This could be explained by optimism bias, a well documented tendency to underestimate the individual risk of the occurrence of a negative event (Weinstein, 1980). This translates into individuals believing that they are less at risk than the average person of health hazards such as having a heart attack, contracting

AIDS, being in a traffic accident or developing cancer (Sharot, 2011; Fontaine and Smith, 1995; Fontaine, 1994; DeJoy, 1989; Perloff and Fetzer, 1986). This might explain why the generic information was successful in increasing awareness about the emitting sources of wood burning, for example, but was not enough to shift behaviour. In contrast, the provision of detailed PM2.5 concentrations and social comparisons through personalised emission profiles could help attenuate this optimism bias by increasing the salience of individual risk to the household and not the average population risk.

The reader should keep in mind external validity limitations. The recruitment of households on a volunteer basis threatens the external validity of our estimated effect size. Households in our sample agreed to install an air quality monitor in order to receive information on their household's air quality as well as recommendations on how to improve it, resulting in a sample that is likely more sensitive to air quality than the total underlying population, leading to an overestimation of the treatment effect if our sample of households reacted more to the treatment. However, it is also possible that our sample has a higher preexisting knowledge of the dangers of wood burning, and would thus have a smaller margin of behavioural change compared to a more representative sample. Generally, this paper sheds light on the effectiveness of information provision in shaping health and environmental behaviour and suggests a strong tool to tackle occasional and auxiliary wood burning pollution. As the use of wood burning is on the rise and expected to increase further following the shift from fossil fuels to renewable energy, policy makers are urged to mitigate the associated increase in indoor and outdoor pollution and inform users of the sanitary consequences of the biomass transition, while limiting unnecessary occasional use (Guercio et al., 2020; Vicente et al., 2020; Mitchell et al., 2017; Chafe et al., 2015; van der Gon et al., 2015; Amann et al., 2005). Policy tools such as regulatory and monetary measures are usually faced with controversy; while wood burning in high income countries is

predominantly used as an auxiliary and occasional heating source (Chafe et al., 2015; Sigsgaard et al., 2015), it is still the least costly method of heating (Martinopoulos, Papakostas and Papadopoulos, 2018; Saffari et al., 2013) and thus the use of an alternative source of heating might be out of reach for low-income households. This is why taxation on wood could be met with re-distributive concerns and might lead to the burning of non-wood materials, often more polluting than certified wood. Meanwhile, subsidies for change-out programs are costly and face low take-up rates (Boso, Oltra and Hofflinger, 2019) especially when wood burning households are not willing to invest in efficient and less polluting equipment for occasional use. Less intrusive policies, such as educational and awareness campaigns are thus proposed as a way to reduce unnecessary wood burning and promote equipment change (Chafe et al., 2015). The findings of this paper shed light on the importance of including tailored and salient information when designing educational campaigns targeting personal exposure to pollution, and occasional wood burning more specifically.

2.8 Tables

Table 2.1: Summary statistics and balance check of household characteristics between the three treatment groups

	All N=281	Control N=94	Information N=93	Information + PEP N=94	C=I	C=I+PEP	I=I+PEP
Panel A: Sociodemographic							
Age	48.94(11.7)	47.9(11.5)	48.1(11.4)	51.0(12.1)	0.889	0.072	0.096.
Household size	3.25(1.32)	3.4(1.4)	3.3(1.2)	3.2(1.3)	0.596	0.325	0.625
Education level:							
Baccalaureate or less	0.1(0.34)	0.2(0.4)	0.1(0.3)	0.1(0.3)	0.141	0.527	0.395
BAC+2 to +4	0.39(0.49)	0.3(0.5)	0.4(0.5)	0.4(0.5)	0.210	0.322	0.787
BAC+5 or more	0.46(0.5)	0.5(0.5)	0.5(0.5)	0.5(0.5)	0.947	0.947	0.894
Monthly income (€):							
Less than 3400	0.2(0.4)	0.2 (0.4)	0.2 (0.4)	0.2 (0.4)	0.590	0.401	0.169
3400 to 5000	0.4(0.48)	0.4 (0.5)	0.3 (0.5)	0.4 (0.5)	0.485	0.954	0.521
More than 5000	0.3(0.47)	0.3 (0.5)	0.4 (0.5)	0.3 (0.5)	0.259	0.963	0.239
Panel B: Health status and attitudes							
Household with resp. problems	0.27(0.44)	0.34 (0.48)	0.22 (0.41)	0.26 (0.44)	0.056*	0.204	0.519
Subjective health status:							
Bad	0.04 (0.2)	0.04 (0.20)	0.05 (0.23)	0.03 (0.18)	0.722	0.702	0.464
Acceptable	0.27(0.45)	0.34(0.48)	0.26(0.44)	0.22(0.42)	0.221	0.075	0.582
Good	0.59(0.49)	0.52 (0.50)	0.55 (0.50)	0.68 (0.47)	0.712	0.025*	0.063
Excellent	0.1(0.3)	0.10 (0.30)	0.14 (0.35)	0.06 (0.25)	0.353	0.422	0.087
Investment in health	68.32(15.92)	69.70 (16.12)	66.91 (17.18)	68.11 (14.62)	0.254	0.478	0.610
Ranking of health in priorities	3.38(1.38)	3.20 (1.31)	3.49 (1.31)	3.45 (1.53)	0.125	0.235	0.817

Table 2.1 – *continued from previous page*

	All N=281	Control N=94	Information N=93	Information + PEP N=94	C=I	C=I+PEP	I=I+PEP
Panel C:							
Environmentalism							
Environmental Attitude	3.68(0.7)	3.57 (0.77)	3.82 (0.63)	3.66 (0.66)	0.016*	0.395	0.087
Environmental Behaviour	0.59(0.24)	0.57 (0.24)	0.60 (0.26)	0.60 (0.21)	0.451	0.403	1.000
Panel D:							
Pollution perception							
Pollution health risk perception	68(21)	70.39 (20.47)	67.80 (19.69)	64.86 (22.27)	0.411	0.102	0.376
Wood burning listed as:							
An outdoor pollution source	0.55(0.5)	0.54 (0.50)	0.49 (0.50)	0.54 (0.50)	0.539	0.953	0.582
An indoor pollution source	0.36(0.5)	0.37 (0.49)	0.32 (0.47)	0.38 (0.49)	0.483	0.984	0.475
Air quality (1-5 score)							
...at home	3.8(1.1)	3.84(1.12)	3.68 (1.09)	3.85(1.06)	0.343	0.969	0.315
...in the neighborhood	3.6(1.3)	3.73(1.27)	3.46(1.28)	3.67(1.25)	0.164	0.762	0.275
...in Île-de-France	2.44(1.2)	2.73(1.32)	2.36(1.14)	2.27(1.16)	0.052*	0.019*	0.648
Panel E:							
Wood burning practices							
Frequency of wood burning:							
More than once a week	0.52(0.5)	0.49 (0.50)	0.57 (0.50)	0.48 (0.50)	0.303	0.885	0.240
More than once a month	0.32(0.47)	0.34 (0.48)	0.29 (0.46)	0.33 (0.47)	0.494	0.878	0.595
Once a month or less	0.17(0.37)	0.17 (0.38)	0.14 (0.35)	0.19 (0.40)	0.589	0.707	0.361
Type of equipment:							
Open fireplace	0.22(0.42)	0.18 (0.39)	0.32 (0.47)	0.19 (0.39)	0.034*	0.944	0.041*
Panel F:							
Indoor Pollution							
Baseline PM2.5	4.96(7.89)	5.41(11.01)	4.67(5.58)	4.82(5.99)	0.520	0.607	0.893

Table 2.1 – *continued from previous page*

	All N=281	Control N=94	Information N=93	Information + PEP N=94	C=I	C=I+PEP	I=I+PEP

Notes: Data from baseline survey. p-values of pairwise t-tests. Mean values are shown and Standard deviation in parentheses. *Significance at 10% level. **Significance at 5% level. ***Significance at 1%. PEP = Personalised Emission Profile.

Table 2.2: Impacts on indoor air quality measured by average indoor PM2.5 levels

	Dependent variable:	
	Average daily PM2.5	
	(1)	(2)
Information (I)	−0.193	0.033
	(0.539)	(0.564)
Infomation + PEP (I+PEP)	−1.315**	−1.175**
	(0.536)	(0.549)
Mean Control Group Group	5.55	5.5
p-value of I=I+PEP	0.040**	0.030**
Baseline controls	No	Yes
Observations	280	277
Adjusted R^2	0.725	0.723

Notes: Data from micro-monitors. Column (1) shows estimates from equation 2.1. Specification in Column (2) includes imbalanced baseline variables as controls: the presence of a household member with respiratory problems, subjective health status, the perceived air quality in the region and wood burning equipment type. Strata fixed effects are used in all regressions.Standard errors (in parentheses) are robust to heteroscedasticity. * Significance at 10% level. ** Significance at 5% level. *** Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.3: Heterogeneous impacts on indoor air quality measured by average indoor PM2.5 levels, by baseline level of indoor pollution

	Dependent variable: Average daily PM2.5 (µg/m^3)			
	Quartiles of baseline PM2.5 levels			
	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)
Information (I)	0.252	−0.010	−0.783*	−0.304
	(0.304)	(0.313)	(0.39)	(2.046)
Information + PEP (I+PEP)	0.214	−0.382	−0.410	−4.911**
	(0.297)	(0.313)	(0.375)	(2.080)
Mean Control Group Group	1.90	2.86	4.17	13.49
p-value for I=I+PEP	0.90	0.25	0.32	0.03**
Observations	70	71	71	68
Adjusted R^2	−0.12	−0.10	0.06	0.64
	Information		Infomation + PEP	
p-value for Q1=Q2	0.86		0.69	
p-value for Q1=Q3	0.49		0.67	
p-value for Q1=Q4	0.71		0.00**	
p-value for Q2=Q3	0.59		0.98	
p-value for Q2=Q4	0.84		0.00**	
p-value for Q3=Q4	0.74		0.00**	

Notes: Data from micro-monitors. Columns (1) to (4) show the treatment effect from equation 2.1 estimated in subsamples of households in the 4 quartiles of baseline PM2.5 levels. The bottom panel shows the p-values of the difference in treatment effects between each pair of quartiles, derived from interactions between each of the quartile dummies and the treatment dummies. Strata fixed effects are used in all regressions. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.4: Heterogeneous impacts on indoor air quality measured by average indoor PM2.5 levels, by outside temperature

	Dependent variable: daily PM2.5 ($\mu g/m^3$)		
	Cold days *temperature* $< 8°C$	Moderate days $8°C <$ *temperature* $< 14°C$	Warm days *temperature* $> 14°C$
	(1)	(2)	(3)
Information (I)	0.010	−0.043	0.385
	(0.388)	(0.507)	(0.661)
Information + PEP (I+PEP)	−0.738**	−1.304***	−0.760
	(0.368)	(0.452)	(0.511)
Mean Control Group	5.05	5.15	4.60
p-value for I=I+PEP	0.03**	0.01**	0.14
Observations	10,338	5,647	789
Adjusted R^2	0.423	0.497	0.546
	Information	Information + PEP	
p-value for Cold=Moderate	0.84	0.19	
p-value for Cold=Warm	0.88	0.68	
p-value for Moderate=Warm	0.65	0.57	

Notes: Data from micro-monitors and Météo France. Columns (1)-(3) show the treatment effects using daily PM2.5 household level data, restricting the observations to days in which a household recorded an outside temperature smaller than $8°C$, between 8 and $14°C$ and above $14°C$, respectively. The bottom panel shows the p-values of the difference of treatment effects between each pair of temperature levels; the p-values shown estimates shown are derived from an interactions between each of the temperature dummies and the treatment dummies. Strata and region fixed effects are included. Standard errors (in parentheses) are robust to heteroscedasticity and clustered at the household and day level. *Significance at 10% level. ** Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.5: Impacts on the number of days that exceed the WHO 24-hour guideline, full sample and by baseline level of indoor pollution

	Dependent variable: Number of days exceeding 24hr WHO PM2.5 limit				
		Quartiles of baseline PM2.5 levels			
	Full sample	Q1	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)
Information (I)	0.401	0.045	0.259	0.01	1.304
	(0.800)	(0.237)	(0.210)	(0.271)	(3.143)
Information + PEP (I+PEP)	−1.440*	0.088	0.081	0.130	−6.461**
	(0.799)	(0.237)	(0.210)	(0.271)	(3.197)
Mean Control Group Group	2.91	0.17	0.12	0.57	12.39
P-value for I=I+PEP	0.02**	0.85	0.41	0.63	0.02**
Observations	281	71	71	71	68
Adjusted R^2	0.702	−0.116	−0.159	0.063	0.658
	Information		Information + PEP		
p-value for Q1=Q2	0.92		0.99		
p-value for Q1=Q3	0.98		0.98		
p-value for Q1=Q4	0.57		0.00***		
p-value for Q2=Q3	0.90		0.98		
p-value for Q2=Q4	0.63		0.00***		
p-value for Q3=Q4	0.55		0.00***		

Notes: Data from micro-sensors. The estimates depict the treatment effects measured using equation 2.1 on the number of days a household records PM2.5 levels higher than the 25 µg/m^3 recommended by the WHO, not to be exceeded more than 3 days a year. Column (1) presents the estimates in the full sample while Columns (2) to (5) present the estimates in subsamples of households in the 4 quartiles of baseline PM2.5 levels. Strata fixed effects are used in all specifications. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile

Table 2.6: Impacts on knowledge of indoor PM2.5 sources

	Dependent variable: Mentioned ... as indoor polluting source (0/1)				
	wood burning	cigarettes	candles	incense	cooking
	(1)	(2)	(3)	(4)	(5)
Information (I)	0.276***	0.121*	0.062	0.017	0.030
	(0.078)	(0.066)	(0.053)	(0.045)	(0.039)
Information + PEP (I+PEP)	0.215***	0.160**	−0.006	0.006	0.0004
	(0.078)	(0.066)	(0.054)	(0.046)	(0.040)
Mean Control Group	0.458	0.117	0.088	0.058	0.044
p-value of I=I+PEP	0.43	0.55	0.21	0.812	0.45
Observations	202	202	202	202	202
Adjusted R^2	0.098	0.097	0.011	0.061	−0.010

Notes: Data from baseline and endline survey. All estimates are derived from OLS regressions (equation 2.3). Controls for baseline response are included in all regressions. Question: "Are you aware of any sources of indoor air pollution in your home or in others? If so, please give one to three examples". Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.7: Impacts on beliefs, knowledge and attitudes towards wood burning and indoor pollution, full sample and by baseline level of indoor pollution

	Dependent variable:						
	(1) Impact of pollution on health (0-100)	(2) Impact of wood burning on indoor pollution (0-100)	(3) Wood burning is a source of outdoor pollution (0/1)	(4) Good practices knowledge (0/1)	(5) Attitude towards wood burning regulation (1-5)	(6) Pleasure derived from wood burning (1-10)	(7) Equipment change intention (0/1)
Full sample							
Information (I)	0.208	6.169*	0.187***	0.125*	0.226	−0.068	−0.011
	(2.795)	(3.142)	(0.070)	(0.066)	(0.182)	(0.274)	(0.061)
Information + PEP (I+PEP)	3.785	9.079***	0.143**	0.129*	0.187	−0.140	−0.049
	(2.802)	(3.142)	(0.070)	(0.067)	(0.181)	(0.273)	(0.061)
Mean Control Group	65.61	60.00	0.47	0.67	3.3	7.64	0.22
p-value of I=I+PEP	0.200	0.360	0.450	0.970	0.840	0.810	0.350
Observations	271	271	271	271	271	271	271
Adjusted R^2	0.268	0.028	0.129	0.012	−0.006	−0.093	−0.001
Quartile 1							
Information	−6.599	5.60	0.253*	0.218*	0.020	−0.642	−0.077
	(5.530)	(4.6)	(0.131)	(0.128)	(0.333)	(0.557)	(0.125)
Information + PEP	3.435	6.13	0.158	0.091	0.043	−0.087	−0.174
	(5.484)	(6.6)	(0.130)	(0.125)	(0.329)	(0.550)	(0.123)
Mean Control Group	65.52	59.30	0.48	0.68	3.43	7.87	0.30
p-value of I=I+PEP	0.240	0.400	0.060	0.090	0.950	0.260	0.540
Quartile 2							
Information	1.076	−2.251	0.264*	0.217*	0.434	−0.050	0.126
	(6.204)	(6.358)	(0.145)	(0.129)	(0.366)	(0.499)	(0.107)
Information + PEP	1.714	5.233	0.099	0.232*	0.242	0.195	−0.117
	(5.964)	(6.206)	(0.141)	(0.125)	(0.358)	(0.487)	(0.104)
Mean Control Group	67.52	64.68	0.44	0.625	3.28	7.24	0.16
p-value of I=I+PEP	0.860	0.720	0.070	0.100	0.240	0.260	0.240
Quartile 3							
Information	8.820*	10.121	0.101	0.072	0.564*	0.189	−0.102
	(4.815)	(6.273)	(0.148)	(0.140)	(0.306)	(0.523)	(0.122)
Information + PEP	9.627*	7.824	0.014	0.048	0.121	−0.032	0.077
	(4.925)	(6.338)	(0.147)	(0.143)	(0.309)	(0.528)	(0.124)
Mean Control Group	63.50	61.05	0.59	0.67	3.23	7.73	0.23
p-value of I=I+PEP	0.070	0.110	0.500	0.610	0.070	0.260	0.410
Quartile 4							
Information	−2.297	11.745**	0.129	−0.008	−0.159	0.018	0.027
	(5.959)	(5.866)	(0.139)	(0.138)	(0.370)	(0.692)	(0.122)
Information + PEP	−2.848	20.243***	0.253*	0.135	0.141	−0.843	−0.070
	(5.902)	(5.805)	(0.138)	(0.138)	(0.366)	(0.685)	(0.121)
Mean Control Group	65.65	53.80	0.35	0.72	3.25	7.80	0.20
p-value of I=I+PEP	0.700	0.050	0.360	0.950	0.670	0.260	0.820
Observations	69	69	69	65	69	69	69

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3). Controls for baseline levels are included in columns (1) and (3). The impact of pollution on health and of wood burning on indoor air pollution (columns (1) & (2)) were measured on a scale from 0-"Not at all impactful" to 100-"Extremely impactful". Column (3) shows the treatment effect on the probability of mentioning woodburning as an outdoor source of pollution and column (4) the probability of mentioning at least one good practice in wood burning management. Respondent's attitudes towards wood burning policy (column (5)) is measured using a score from 1-"Not at all in favor" to 5-"Completely in favour", while the pleasure derived from lighting a fireplace (column (6)) is measured on a scale from 0-"No pleasure" to 10-"A lot of pleasure". The upper panel shows treatment effects estimated on the full sample, while the bottom 4 panels show the estimates on subsamples of quartiles of baseline PM2.5. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.8: Impacts on declared use of wood burning and intention of future use, full sample and by baseline level of indoor pollution

	Declared frequency of wood burning						
	Past winter			Next winter			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Once a month or less	More than once a month	Once a week or more	Never	Once a month or less	More than once a month	Once a week or more
Full sample							
Information (I)	0.036	0.043	−0.082	0.012	0.089	0.020	−0.138**
	(0.053)	(0.065)	(0.057)	(0.039)	(0.056)	(0.066)	(0.056)
Information + PEP (I+PEP)	−0.010	0.066	−0.062	0.034	0.035	0.066	−0.140**
	(0.053)	(0.064)	(0.057)	(0.039)	(0.056)	(0.066)	(0.056)
Mean Control Group	0.170	0.340	0.490	0.060	0.160	0.300	0.490
p-value of I=I+PEP	0.390	0.720	0.730	0.630	0.490	0.970	0.340
Observations	267	267	267	268	267	267	267
Adjusted R^2	0.388	0.130	0.410	−0.004	0.092	0.122	0.428
Quartile 1							
Information	0.012	−0.002	−0.053	0.012	0.082	−0.014	−0.097
	(0.091)	(0.127)	(0.108)	(0.038)	(0.123)	(0.140)	(0.106)
Information + PEP	0.050	0.016	−0.100	0.031	0.074	0.048	−0.187*
	(0.090)	(0.125)	(0.107)	(0.038)	(0.122)	(0.138)	(0.105)
Mean Control Group	0.30	0.35	0.35	0.17	0.39	0.39	0.17
p-value of I=I+PEP	0.680	0.890	0.670	0.950	0.660	0.400	0.950
Observations	68	68	68	271	68	68	68
Quartile 2							
Information	0.027	0.102	−0.160	0.095	0.196*	−0.026	−0.247**
	(0.114)	(0.138)	(0.105)	(0.061)	(0.111)	(0.140)	(0.110)
Information + PEP	−0.025	0.318**	−0.275***	0.043	0.084	0.150	−0.269**
	(0.111)	(0.133)	(0.101)	(0.059)	(0.108)	(0.135)	(0.106)
Mean Control Group	0.28	0.28	0.44	0.16	0.36	0.48	0.16
p-value of I=I+PEP	0.660	0.130	0.290	0.330	0.220	0.850	0.330
Quartile 3							
Information	0.176	0.098	−0.178	0.034	0.083	0.087	−0.181
	(0.117)	(0.128)	(0.113)	(0.105)	(0.125)	(0.127)	(0.111)
Information + PEP	0.011	0.033	−0.040	0.126	0.023	0.030	−0.126
	(0.118)	(0.128)	(0.115)	(0.106)	(0.126)	(0.127)	(0.113)
Mean Control Group	0.32	0.18	0.50	0.18	0.18	0.55	0.18
p-value of I=I+PEP	0.160	0.610	0.220	0.630	0.650	0.620	0.630
Quartile 4							
Information	−0.121	0.033	0.077	−0.100*	−0.013	0.083	−0.029
	(0.097)	(0.114)	(0.122)	(0.053)	(0.083)	(0.120)	(0.120)
Information + PEP	−0.109	−0.104	0.209*	−0.100*	−0.008	0.032	0.064
	(0.094)	(0.112)	(0.119)	(0.052)	(0.080)	(0.119)	(0.117)
Mean Control Group	0.25	0.30	0.45	0.10	0.25	0.55	0.10
p-value of I=I+PEP	0.160	0.610	0.220	0.630	0.650	0.620	0.630

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3) on the declared frequency of use of wood burning equipment the past winter (columns (1) to (3)) and the intention of use next winter (columns (4) to (7)). The responses of the categorical variable were turned into dummy variables and used as the outcome variables in separate regressions. For all regressions, declared baseline response is added as control.The upper panel shows treatment effects estimated on the full sample, while the bottom 4 panels show the estimates on subsamples of quartiles of baseline PM2.5. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.9: Impacts on the frequency of wood burning and other polluting activity in the last week

	Dependent variable: declared weekly frequency of						
	(1) wood burning	(2) cigarette	(3) ecigarette	(4) candles	(5) incense	(6) dusting	(7) Polluting activity
Information (I)	−0.095	0.542	0.711	0.109	−0.042	0.043	1.271
	(0.371)	(0.625)	(0.643)	(0.135)	(0.235)	(0.283)	(1.150)
Information + PEP (I+PEP)	0.141	−0.124	−0.128	−0.011	0.048	−0.024	−0.106
	(0.371)	(0.621)	(0.639)	(0.135)	(0.235)	(0.283)	(1.144)
Mean Control Group	1.59	0.60	0.62	0.33	0.30	1.82	5.30
p-value of I=I+PEP	0.530	0.290	0.190	0.370	0.700	0.810	0.230
Observations	268	265	266	265	268	268	261
Adjusted R^2	−0.006	−0.003	−0.0001	−0.004	−0.007	−0.007	−0.001

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3). Question: "In the last week, How many times inside your dwelling has someone...burned wood/smoked a cigarette/ smoked an e-cigarette/ lit a candle/ lit incense/ dusted". Polluting activity (column (7)) designates the number of times a household engaged in *any* of the mentioned polluting behaviours over the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.10: Impacts on the frequency of air quality improving activities in the last week

	Dependent variable: declared weekly frequency of	
	Using the ventilation hood	Opening windows
	(1)	(2)
Information (I)	0.160	0.173
	(0.715)	(0.486)
Information + PEP (I+PEP)	−0.277	−0.362
	(0.709)	(0.481)
Mean Control Group	4.25	6.6
p-value of I=I+PEP	0.539	0.270
Observations	271	270
Adjusted R^2	−0.006	−0.003

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3). Question:"In the last week, How many times inside your dwelling has someone...used the ventilation hood/Opened the windows for aeration". Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.11: Impacts on the incidence of wood burning and other polluting activity in the last week

	Dependent variable: declared weekly incidence of					
Polluting activity	wood burning	cigarette	ecigarette	candles	incense	dusting
	(1)	(2)	(3)	(4)	(5)	(6)
Information (I)	−0.073	−0.010	−0.009	0.023	−0.025	0.020
	(0.075)	(0.036)	(0.038)	(0.043)	(0.063)	(0.054)
Information +PEP (I+PEP)	−0.043	−0.013	−0.023	0.020	−0.075	0.047
	(0.074)	(0.035)	(0.037)	(0.043)	(0.063)	(0.054)
Mean Control Group	0.50	0.07	0.08	0.26	0.08	0.82
p-value of I=I+PEP	0.690	0.930	0.700	0.430	0.940	0.620
Observations	271	268	269	271	268	271
Adjusted R^2	−0.004	−0.007	−0.006	−0.006	−0.002	−0.005

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3). Question:"In the last week, How many times inside your dwelling has someone...burned wood/smoked a cigarette/smoked an e-cigarette/lit a candle/lit incense/dusted". The dependent variable measures the incidence of polluting activity and is an indicator variable that takes the value 1 if the household declared undertaking the activity at least once in the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.12: Impacts on the incidence of air quality improving activities in the last week

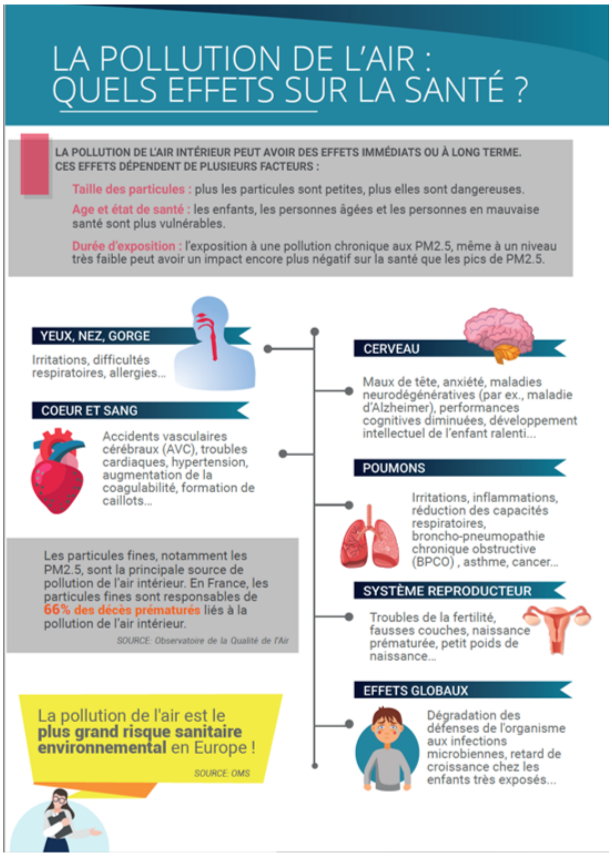
	Dependent variable: declared weekly incidence of	
	Using the ventilation hood	Opening windows
	(1)	(2)
	Dependent variable:	
	Using the ventilation hood	Opening windows
	(1)	(2)
Information (I)	0.019	0.011
	(0.067)	(0.016)
Information + PEP	0.017	−0.011
	(0.067)	(0.016)
Mean Control Group	0.71	0.99
p-value I=I+PEP	0.980	0.170
Observations	271	270
Adjusted R^2	−0.007	−0.0003

Notes: Data from endline survey. All estimates are derived from OLS regressions (equation 2.3). Question:"In the last week, How many times inside your dwelling has someone...used the ventilation hood/ Opened the windows for aeration".The dependent variable measures the incidence of polluting activity and is an indicator variable that takes the value 1 if the household declared undertaking the activity at least once in the past week. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

2.A Appendix

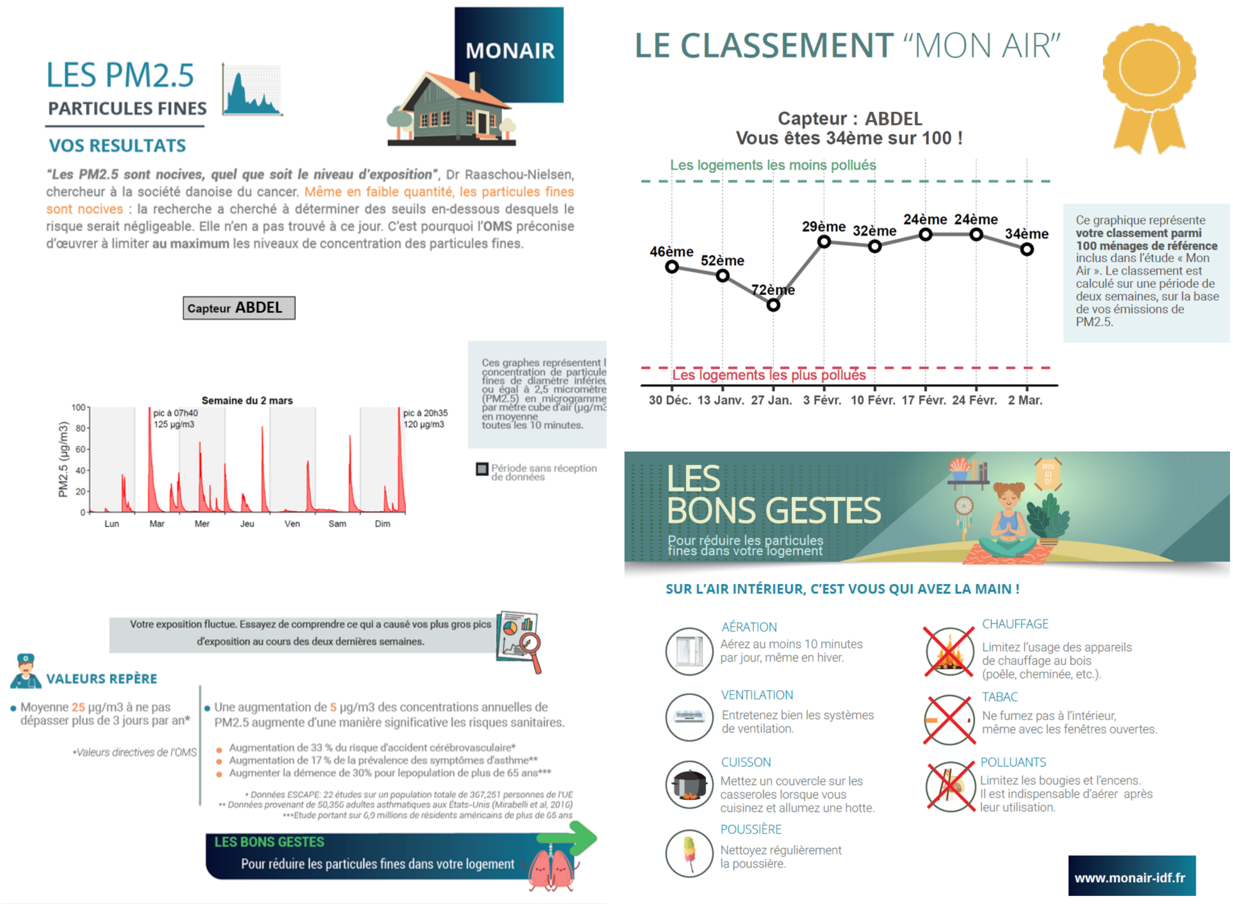
Figure 2.A1: Example of a weekly informational leaflet (*Information* treatment)

(a) Weekly cover of informational leaflet



(b) Weekly info-graphics

Figure 2.A2: Example of a weekly Personalised Emission Profile



(a) Weekly PM2.5 emission graph

(b) Weekly social comparison graph

Table 2.A1: Impact of the treatments on the probability of attrition

	Dependent variable:
	Missing endline variables (0/1)
Information (I)	−0.000
	(0.030)
Information + PEP (I+PEP)	0.011
	(0.030)
p-value of I=I+PEP	0.724
Observations	282

Notes : The dependent variable "Missing endline variables" measures the incidence of attrition; it takes the value 0 if the household answered the endline questionnaire and 1 if we received no answer. Coefficients estimated using OLS regression. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level. PEP = Personalised Emission Profile.

Table 2.A2: Summary descriptives table by quartiles of baseline PM2.5 levels

	Quartiles 1 - 3 N=213	Quartile 4 N=68	p-value of Q1-3=Q4
Age	49.20 (11.82)	48.61 (11.70)	0.717
Household size	3.26 (1.33)	3.28 (1.24)	0.941
<u>Level of education</u>			
Baccalaureate or less	0.13 (0.34)	0.13 (0.34)	0.946
BAC+2 to +4	0.39 (0.49)	0.39 (0.49)	0.997
BAC+5 or more	0.47 (0.50)	0.46 (0.50)	0.982
<u>Income level</u>			
Less than 3400	0.16 (0.37)	0.26 (0.44)	0.086*
3400 to 5000	0.40 (0.49)	0.35 (0.48)	0.475
More than 5000	0.35 (0.48)	0.26 (0.44)	0.153

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Table 2.A2 – *continued from previous page*

	Quartiles 1 - 3 N=213	Quartile 4 N=68	p-value of Q1-3=Q4
Polluting activity			
Presence of smoker in the household	0.061 (0.23)	0.29 (0.45)	0.00***
Use of incense	0.13 (0.33)	0.11 (0.31)	0.65
Presence of a pet	0.50 (0.50)	0.56 (0.49)	0.46
Wood burning frequency			
Once a week or more	0.48 (0.50)	0.65 (0.48)	0.010**
More than once a month	0.34 (0.47)	0.26 (0.44)	0.230
Once a month or less	0.19 (0.39)	0.09 (0.28)	0.022**
Wood burning equipment type			
Open fireplace	0.22 (0.42)	0.23 (0.43)	0.878
Pollution health risk perception	69.03 (20.20)	63.30 (23.94)	0.078*
Investment in health	67.99 (15.73)	67.77 (16.66)	0.925
Wood burning listed as outdoor pollution source	0.56 (0.50)	0.49 (0.50)	0.308
Household member with respiratory problems	0.27 (0.44)	0.25 (0.44)	0.955
Ranking of health in priorities	3.34 (1.42)	3.48 (1.26)	0.452
Subjective health status			
Bad	0.04 (0.20)	0.04 (0.21)	0.891
Acceptable	0.24 (0.43)	0.38 (0.49)	0.037**
Good	0.61 (0.49)	0.52 (0.50)	0.213
Excellent	0.11 (0.32)	0.06 (0.24)	0.124

Notes: Data from baseline survey. p-values estimated using independent samples t-tests. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level.

Table 2.A3: Correlation between indoor levels of PM2.5 and self-reported behavior

	Dependent variable:
	Average daily PM2.5
Equipment type	
Closed fireplace or insert	-3.255^{**}
	(1.279)
Wood stove	-2.902^{**}
	(1.368)
Pellet stove	-5.820^{**}
	(2.426)
Wood burning frequency baseline	
More than once a month	-1.131
	(0.977)
Once a month or less	-3.701^{***}
	(1.278)
Household Income	
3400 to 5000	-3.311^{***}
	(1.256)
More than 5000	-4.051^{***}
	(1.324)
Education	
BAC+2 to +4	0.517
	(1.407)
BAC+5 or more	0.235
	(1.457)
Declared frequency in past week (0/1)	
Wood burning	0.997
	(0.721)
Cigarette	18.142^{***}
	(1.572)
E-cigarette	-2.245
	(1.580)
Candles	-0.470
	(0.903)
Encens	0.414
	(1.299)
Dusting	0.869
	(1.047)
Ventilation hood	-0.845
	(0.792)
Window opening	0.623
	(3.377)
Observations	281
Adjusted R^2	0.068
Residual Std. Error	6.576 (df = 260)
F Statistic	2.137^{***} (df = 15; 230)

Notes: estimates from OLS regression of average daily PM2.5 regressed on households characteristics. Standard errors (in parentheses) are robust to heteroscedasticity. *Significance at 10% level. **Significance at 5% level. ***Significance at 1% level.

Chapter 3

Socioeconomic status, time preferences and pro-environmentalism*

3.1 Introduction

Environmental issues are emblematic cases of intertemporal problems: they involve resource dilemmas where a short-term cost is incurred for a benefit that only comes in the future (Kortenkamp and Moore, 2006). Preserving forests or fresh water for example, yields immediate costs, such as refraining from using a resource that is available, while the majority of the benefits are only felt in the future. Cutting one's individual carbon emissions by limiting the use of one's car or reducing heating at home also implies self-restraint in the present, in order to maintain decent life conditions for future generations, or for oneself in the future.

Given the temporal nature of environmental issues, individual variations in time preferences may have an effect on people's willingness to engage in environmental

*This chapter was co-authored with Coralie Chevallier, Aurore Grandin, Léonard Guillou.

actions (Van Vugt, Griskevicius and Schultz, 2014). In line with this idea, a meta-analysis by Milfont, Wilson and Diniz (2012) shows that there is a link between time orientation and pro-environmental attitudes and behaviour, such that individuals with a future-oriented time perspective are on average more engaged in environmental preservation than present-oriented individuals. Identifying the factors that influence time preferences is therefore of central importance to shed light on the variability of pro-environmental attitudes and behaviour.

Several socio-demographic factors play a role in explaining variations in time preferences (Reimers et al., 2009). In particular, multiple studies have now demonstrated that low socioeconomic status (SES) orients individual time preferences towards the present, resulting in a tendency to favour short-term behaviours. Time preferences are typically measured using temporal discounting tasks, in which participants are asked to choose between smaller, more immediate rewards, and larger but more delayed rewards (Green, Fry and Myerson, 1994; Frye et al., 2016). Using these tasks, researchers have shown that people with low incomes and educational levels discount more steeply than people with a higher SES (Hausman, 1979; Lawrance, 1991*a*; Green et al., 1996; Harrison, Lau and Williams, 2002*a*; Reimers et al., 2009; Enzler, Diekmann and Meyer, 2014). Research documenting increases in impatience due to natural disasters and climate-driven income shocks provides support to the hypothesis that this association between SES and time preferences is causal (Cassar, Healy and Von Kessler, 2017*a*; Di Falco et al., 2019*a*; Tanaka, Camerer and Nguyen, 2010*a*). These empirical results are congruent with recent theoretical papers arguing that differences in time preferences play an important role in accounting for socioeconomic gradients in a range of individual behaviours (Bickel et al., 2014; Mani et al., 2013*a*; Pepper and Nettle, 2017; Sheehy-Skeffington and Rea, 2017).

Given that socioeconomic conditions have an impact on time preferences on the

one hand, and given that future-oriented individuals tend to engage more in pro-environmental actions on the other, SES may have an effect on pro-environmental behaviour via time preferences. In line with this idea, social scientists have long noted an association between SES and pro-environmental attitudes and behaviour in large-scale reviews (Diamantopoulos et al., 2003; Hines, Hungerford and Tomera, 1987). More recent research confirms that green consumption, recycling, signing petitions, or engaging in environmental organisations are more widespread among high SES individuals (Kennedy, Baumann and Johnston, 2018; Kennedy and Givens, 2019; Guerin, Crete and Mercier, 2001*a*), and multilevel analyses have shown that this pattern is found in countries around the world (Pisano and Lubell, 2017; Marquart-Pyatt, 2008; Franzen and Meyer, 2009; Haller and Hadler, 2008). Other studies have found that despite the fact that individuals of lower SES are more worried about the risks associated with environmental hazards, they report being less willing to act for the environment than individuals with higher incomes and educational attainments (Marquart-Pyatt, 2012; Lo, 2016*a*).

Financial capacities play a direct and rather obvious role in this association, because many pro-environmental behaviours are costly. For example, having more money decreases the relative burden of green taxes and facilitates access to eco-friendly products. Symmetrically, pro-environmental behaviours that are cost-effective, such as energy-saving behaviours and the use of public transport, are more frequent among low SES individuals (Blankenberg and Alhusen, 2018; Trotta, 2018). Beyond this mechanical impact of income, engagement in pro-environmental behaviour is also influenced by other factors associated with SES. For instance, social scientists and economists have shown that green consumption is also a matter of signalling affiliation to a high social class (Delgado, Harriger and Khanna, 2015; Kennedy and Givens, 2019; van der Wal, van Horen and Grinstein, 2016).

The goal of our paper is to test whether psychological preferences also contribute

to the association between SES and pro-environmental behaviour. Recent theoretical frameworks, such as the one proposed by Pepper and Nettle (2017), indeed emphasize the role of time preferences in creating social gradients in a range of real-life decisions that have a strong temporal component, such as investment in education or preventive health. However, these theories have not been applied to environmental behaviour yet, and the idea that the relationship between SES and pro-environmentalism is mediated by time preferences has not been tested.

In this paper, our general hypothesis is that pro-environmental behaviour and willingness to protect the environment are less common among people with a lower SES in part because their temporal discounting is higher. In other words, we hypothesize that the relationship between SES and pro-environmental behaviour is partially mediated by temporal discounting. In our first study, we leverage existing data collected on a French large-scale sample to test the association between SES and pro-environmental attitudes. Our second study tests a mediation model between SES, pro-environmentalism and temporal discounting. Finally, our third study investigates the causal impact of an information shock about relative income on temporal discounting and pro-environmentalism.

3.2 Study 1 : Socioeconomic status and pro-environmental attitudes in a French sample

In study 1, we capitalized on existing data collected by the Center of political research of Sciences Po (CEVIPOF) from a large sample of the French population. We examined whether SES was associated with pro-environmental attitudes. Before analysing the data, our hypotheses, methods, and analysis plan were pre-registered in the Open Science Framework (OSF): `https://osf.io/qav9x`.

Materials and Methods

Participants

The original dataset contains 17 survey waves, ranging from November 2015 to November 2017. For the purposes of this study, we focused on data regarding respondents' environmental attitudes and merged them with information about respondents' SES. The final analysis includes participants with complete data for environmental and socioeconomic variables up to wave 8 (N = 17,070). Following our pre-registered exclusion criterion, we excluded 1,132 respondents who had answered "I don't know" to the environmental items. 14 participants who had answered "I don't know" to the household income question were also excluded (this exclusion criterion had been forgotten in the pre-registration, but matches the one used for the environmental variables). This resulted in a final dataset of 15,924 participants, with 55.7% women and age range = 16-97 years (M = 47.33, SD = 15.32). Mean monthly income was comprised between €2,250 and €2,999 and 53% of the sample had a higher education degree.

Measures

- **Socioeconomic Status**

Objective SES was assessed using level of education and monthly net household income, z-transformed and summed. *Subjective SES* was assessed using z-transformed perceived financial ease, measured with a single item asking respondents how they were doing with their household income. Subjective perception of one's SES plays an important role in predicting disparities in many life domains (Kraus and Stephens, 2012). For example, several medical studies have shown that the association between subjective SES and health outcomes persists after controlling for education and income (Cené et al., 2016; Ghaed and Gallo, 2007). All the original questions in

French, their English translation and the waves during which they were collected are available in the OSF-folder for this study (https://osf.io/9ube8/).

- **Environmental attitudes**

Pro-environmentalism. Pro-environmentalism was measured with the following survey question: "How important are the following issues to you personally? 1) health insurance, 2) social welfare, 3) pensions, 4) fighting unemployment, 5) purchasing power, 6) crime, 7) the environment, 8) immigration, 9) terrorism, 10) the European Union, 11) the competitiveness of companies established in France". This question was asked in wave 8 and in a couple of later waves. Since attrition grows from one wave to the next, we focused on wave 8, which provides the largest sample for this question. To compute participants' pro-environmentalism, we built a score that captures their interest in environmental issues (as measured by item 7), relative to their overall interest in social and political matters (as measured by all items combined). For each participant, the pro-environmentalism score therefore corresponds to a ratio of the raw score in response to issue 7 over the mean of the scores provided on all issues. This transformation was added because raw responses to item 7 confound participants' general interest for political matters and their specific interest for the environment, which is the construct we ultimately care about.

Willingness to increase green taxes and public spending. We also looked at items measuring people's willingness to increase public spending for the environment, to fight climate change and their willingness to increase taxes on polluting activities (see the OSF-folder: https://osf.io/9ube8/). These items were pre-registered as secondary outcomes, because we reasoned that questions relative to public spending and taxes are more likely to be confounded by political orientation than questions tapping general pro-environmental attitudes.

All items were rated on a five-point scale. They were z-transformed and coded

so that the highest scores indicated a pro-environmental position. All three items relative to public spending and taxes were then summed to create a composite score measuring "willingness to increase green taxes and public spending" ($\alpha = .73$, average inter-item correlation $= 0.47$).

Statistical analyses

Our main analyses were pre-registered and carried out in R. We conducted simple linear regressions, with the following specification:

$$Environmental\ attitudes_i = \beta_0 + \beta_1 SES_i + \epsilon \tag{3.1}$$

The associations between the environmental variables and objective and subjective SES were assessed separately with this same linear model. In addition, to control for the effect of political orientation and other potentially confounding variables, we also conducted supplementary unregistered analyses, with the following specification:

$$\begin{gathered} Environmental\ attitudes_i = \beta_2 + \beta_3 SES_i + \beta_4 Age_i + \beta_5 Gender_i + \\ \beta_6 Political\ position_i + \epsilon \end{gathered} \tag{3.2}$$

Participants' political position was measured with a question that asked them to indicate where they stood on a scale of 0 to 10, where 0 is left and 10 is right.

Results

Pro-environmentalism was positively and significantly associated with objective SES ($\beta = 0.09$, $p < .001$) and subjective SES ($\beta = 0.07$, $p < .001$, see Table 3.1). There was also a positive association between SES and willingness to increase green taxes and public spending (objective SES: $\beta = 0.06$, $p < .001$; subjective SES: $\beta = 0.04$, $p < .001$, see Table 3.1). Both environmental variables remained positively correlated

with SES when controlling for age, gender and political orientation (see Table 3.A3 in the Appendix).

The results obtained with education and income as separate variables can be found in the correlation matrix in the Appendix (see Table 3.A2). Both pro-environmentalism and willingness to increase green taxes and public spending were correlated with educational level, but only pro-environmentalism was significantly correlated with income. Further analyses indicated that the different items that make up the composite willingness score were all positively correlated with education, but that their relationships with income were inconsistent: willingness to increase public spending for the environment was negatively correlated with income (r $= -0.024$, $p = .002$) and willingness to increase public spending to fight climate change was not correlated with income (r $= -0.006$, $p = .413$). Only willingness to increase taxes on polluting activities was positively correlated with both income (r $= 0.042$, $p < .001$) and education (r $= 0.083$, $p < .001$).

Discussion

In this study, we found that participants' level of pro-environmentalism relative to other socio-political issues was significantly correlated with their SES. There was also a positive association between SES and willingness to increase green taxes and public spending. Globally, these results suggest that willingness to act for the environment is stronger among higher SES individuals.

Arguably, a measure of willingness to increase green taxes and public spending is not strictly equivalent to willingness to act for the environment. The positive correlation between SES and willingness to increase green taxes and public spending could be partly due to the fact that richer individuals have a higher acceptance of taxes, simply because they have higher financial capacities. Supporting this view, a recent survey conducted with a representative sample of French adults indicates that

low-income individuals are more likely to think that taxes are too high, compared to high-income individuals (Forsé and Parodi, 2015).

However, the present study provides evidence that the association between environmental attitudes and SES is not only a matter of willingness to pay and tax acceptance: the positive correlation between SES and pro-environmentalism suggests that, in France at least, higher SES individuals also give higher priority to environmental issues compared to other socio-political issues, such as health insurance or immigration.

On the whole, these analyses provide support for our hypothesis, but they are only a first step, since they are not sufficient to test the entire mediation model. We were limited by the dataset, which contained no measure of time preferences. In addition, there was no behavioural data, and the environmental variables were potentially confounded by financial and political factors. In study 2, we test the mediation model using an online discounting task combined with relevant questionnaire data.

3.3 Study 2 : Socioeconomic status, time preferences and pro-envrionmental attitudes

The goal of Study 2 was to test whether time preferences partially mediate the relationship between SES and pro-environmental attitudes and behaviour. As in Study 1, our hypotheses, methods, and analysis plan were pre-registered (a first pre-registration focused on the replication of the association between SES and temporal discounting was made (`https://osf.io/452zr`) and a second pre-registration was added to specify our mediation hypotheses: `https://osf.io/58rn2`). Data, materials, and the R script used to analyse the data are also available in the OSF-folder for this study (`https://osf.io/28zkg/files/`).

Besides the measurement of time preferences, one important aspect of this second study is the use of a measure of pro-environmental behaviour. Even though environmental attitudes are good predictors of pro-environmental behaviour, important value-action gaps and intention-to-action gaps are widely documented (Kollmuss and Agyeman, 2002*b*; Lavergne and Pelletier, 2015; Maki et al., 2019). Using direct measures of pro-environmental behaviour is therefore important to better understand the factors that influence actual decision-making (Clements et al., 2015; Oliphant, Jaynes and Moule Jr, 2020).

Materials and Methods

Participants

We conducted a power analysis with G*Power (version 3.1.9.3), which determined that a sample of at least 643 participants was sufficient to detect an effect size $f^2 = 0.0122$ with 80% power. This effect size was computed based on the mean of two correlation coefficients reported by Reimers et al. (2009), who found a Spearman correlation of -0.09 between temporal discounting and income, and of -0.13 between temporal discounting and education. We recruited additional participants to compensate for attrition, resulting in a dataset of 765 participants.

Following our pre-registered exclusion criteria, we removed 9 participants who had failed one or more catch trials in the temporal discounting task. In addition, 49 participants who had responded too fast (< 500 ms) or too slowly (> 2 minutes) to single question screens, and 29 participants who responded too fast (< 3 s) or too slowly (> 5 minutes) to the other survey pages were removed from our analyses. We also excluded 14 participants who did not provide their income. Finally, we added an unregistered exclusion criteria for participants who reported outlier income values (N = 14). Personal monthly incomes above £12,500 were considered as likely reporting

mistakes, and correspond to outlier data points (more than 2SD deviation from the mean).

Our final dataset includes 650 participants (70% females) aged between 21 and 77 years (M = 39 years; SD = 12.8). Participants had an average total monthly income of £935, ranging from £0 to £12,000 (SD = 1,187, see Table 3.4). Participants' educational level was quite high: only 17 participants did not finish high school, while 64% of them had either completed college or obtained a postgraduate degree.

Measures

We presented the questionnaire and discounting task using Qualtrics (`https://www.qualtrics.com`). After providing informed consent, participants filled out the socio-demographic questionnaire. Then, they continued with the discounting task, followed by the measures of pro-environmental attitudes and behaviour.

- **Socioeconomic status**

Our measure of participants' *objective SES* was a single variable combining level of education and personal monthly income. We chose to ask respondents about their personal income rather than their household overall income because Micklewright and Schnepf (2010) have shown that questions about household income induce lower response rates and produce lower quality data. Participants were asked to report their personal monthly income in a free-text box, in order to avoid unintentional priming effects that can arise with the use of income brackets (Haisley, Mostafa and Loewenstein, 2008). Participants were asked to report their level of education on a 6-point scale. Income and level of education were z-transformed and summed to create the unique variable of objective SES.

As in the previous study, we included a measure of *subjective SES*, but this time we used a composite variable combining a scale from Griskevicius et al. (2013) and

the MacArthur Scale of Subjective Social Status (a 10-rung ladder developed by Adler et al., 2000). Griskevicius et al.'s (2013) scale includes three items: *In the past few years: (a) My family and I have had enough money for things, (b) I have lived in a relatively wealthy neighborhood, (c) I have felt relatively wealthy compared to other people in my neighborhood.* A single index was obtained by summing individual scores across the three items ($\alpha = .68$, mean inter-item correlation = .41). We adapted the MacArthur scale in the following way: *"Think of this ladder as representing where people stand in the United Kingdom. At the top of the ladder are the people who are the best off, those who have the most money, most education, and best jobs. At the bottom are the people who are the worst off, those who have the least money, least education, and worst jobs or no job. Where would you place yourself on the ladder?"*. Participants' response to this scale and the index based on Griskevicius et al.'s (2013) scale were z-transformed and summed to create a unique variable of subjective SES. The detailed list of all socioeconomic variables is available in the OSF-folder for this study (`https://osf.io/7v3hs/`).

- **Pro-environmental attitudes**

Pro-environmental attitudes are multidimensional and there is a large number of measures in the literature. In an effort to synthesize these various scales, Milfont and Duckitt (2010) developed the Environmental Attitudes Inventory, which comprises twelve specific scales that capture the main dimensions highlighted by previous research, such as enjoyment of nature, environmental fragility or support for interventionist conservation policies. The present article focuses on attitudes related to willingness to act for the environment. In Study 2, we assessed these attitudes using two 10-item scales from the Environmental Attitudes Inventory (Environmental movement activism and Personal conservation behaviour). All items are listed in Table 3.A1 in the Appendix.

- **Pro-environmental behaviour**

A donation question was included at the end of the experiment. We drew on recent works showing that a non-hypothetical donation to an environmental nonprofit organization is a valid measure of pro-environmental behaviour (Eby, Carrico and Truelove, 2019; Clements et al., 2015). Following Ackermann et al. (2014), we offered participants a choice between different charitable causes rather than specific nonprofit organizations, to avoid biased responses from individuals with strong feelings regarding a particular organization. The six different causes were presented in a random order to counter order effects. To avoid the bias that lower income participants have less money to give, we told participants that a donation would be made on their behalf to a cause of their choosing (see Eby, Carrico and Truelove, 2019). Participants were informed that we would give 10p to a charity for every person that participated in our study, and that they could choose their two favourite causes out of six options: *Reforestation programmes, Food aid for the homeless, Medical cancer research, Care for the elderly, Emergency and disaster relief, Education in developing countries*. Answers were transformed into a binary variable (presence of the cause "Reforestation programmes" among the two choices = 1, absence = 0).

- **Temporal discounting**

The temporal discounting task was based on Frye et al. (2016). Participants had to complete three blocks of an intertemporal choice task with varying delays and amounts. Each block consisted of six binary choice trials. The task ended with two catch trials, resulting in a total of 20 trials. In the first block, participants had the choice between a smaller reward in three days, and a larger reward in three weeks. In the second and third blocks, the later delay was set to three months and two years respectively. As in Haushofer, Schunk and Fehr (2013), possible serial correlations and order effects in participants' responses were controlled for by randomising the order of

trials across blocks. The position of the sooner smaller and larger later alternatives on the screen (top vs. bottom) was also randomised across trials to control for possible position effects.

The monetary choices presented to participants were hypothetical. One concern might be that they may not be sufficiently motivated to give thoughtful answers when answering hypothetical questions. However, no clear and systematic differences have been identified when comparing real and hypothetical rewards in discounting tasks (Johnson and Bickel, 2002; Coller and Williams, 1999; Kirby and Maraković, 1995). Moreover, discount rates measured with hypothetical choices in a laboratory setting have been found to correlate with real-world measures of impulsivity such as smoking, overeating, and debt repayment (Chabris et al., 2008; Hardisty et al., 2013; Meier and Sprenger, 2012; Reimers et al., 2009).

The later reward was kept constant (at 70£ as in Reimers et al., 2009), while the smaller reward was adjusted according to participants' choices. The adjustment was based on a bisection algorithm, following Frye et al. (2016). As recommended by the authors, the adjustment for the upcoming trial was always equal to the maximum amount multiplied by $2^{(-n)}$, where n is the trial number for the current adjustment. Such a procedure allows for the identification of various individual indifference points for each participant. An indifference point corresponds to the magnitude of the smaller–sooner reward at which a participant shows no preference for either the smaller–sooner or later–larger reward (Scholten et al., 2019). It can be used for the computation of a discount rate.

The method that we chose to compute respondents' discount rates is based on the computation of the area under the curve (AUC) of the empirical discounting function (see Myerson, Green and Warusawitharana, 2001; Frye et al., 2016). The empirical discounting function is defined by the various indifference points evidenced by the discounting task. The AUC between two points on the curve is calculated as

$[(x_2 - x_1)[(y_1 + y_2)/2]$, where x_1 and x_2 are the successive delays and y_1 and y_2 are the indifference points for those delays. In the present study, the AUC between 3 weeks and 3 months and the one between 3 months and 2 years were summed, resulting in a single value of AUC per participant. Lower values of the AUC indicate a steeper discount rate.

Statistical analyses

Regression analyses were conducted relying on the three step procedure set forth by Baron and Kenny (1986) to detect a mediation effect. The regression models had the following specifications:

$$Environmentalism = \beta_{10} + \beta_{11} SES + \epsilon \tag{3.3}$$

$$DiscountRate = \beta_{12} + \beta_{13} SES + \epsilon \tag{3.4}$$

$$Environmentalism = \beta_{14} + \beta_{15} SES + \beta_{16} DiscountRate + \epsilon \tag{3.5}$$

Where *Environmentalism* refers alternatively to pro-environmental attitudes and behaviour; *SES* refers alternatively to objective or subjective SES; and *Discount Rate* corresponds to the area under the curve (AUC). We used an OLS regression model for every equation, except for pro-environmental behaviour, for which we used a Logit regression.

Following Baron and Kenny's (1986) approach, a mediation effect exists if coefficients β_{11} and β_{13} in equations (3) and (4) are significant, and if coefficient β_{15} in equation (5) is not significant: in other words, there is a mediation when the predictor-outcome effect becomes non-significant once the mediator is added to

the model. Partial mediation is established when the effect of the predictor on the outcome only weakens once the mediator is added. However, this approach does not formally test the significance of the mediating effect and does not assess its size. Researchers have recommended that other methods, such as nonparametric testing procedures, should be used for this purpose (Aguinis, Edwards and Bradley, 2016; Preacher and Hayes, 2004; Holmbeck, 2002). We derived percentile-based confidence intervals with the bootstrap, relying on R mediation package (see Tingley et al., 2014).

Results

Descriptive statistics for key variables are reported in Table 3.4. Tables 3.2 and 3.3 provide the regression and bootstrap estimates for the full model.

Mediation analysis

For the first step of the mediation analysis, environmental variables were regressed on socioeconomic variables. We found a positive and significant relationship between self-reported pro-environmental attitudes and SES (objective SES: $\beta = 0.09$, $p = .026$; subjective SES: $\beta = 0.08$, $p = .035$, see Table 3.2). However, our measure of pro-environmental behaviour was not correlated with either objective or subjective SES (see Table 3.A4 in the Appendix).

For the second step of the mediation analysis, we found the expected association between SES and temporal discounting: the area under the discounting curve was positively correlated with objective ($\beta = 0.15$, $p < .001$) and subjective SES ($\beta = 0.17$, $p < .001$, see Table 3.2). Since lower values of the area under the curve indicate steeper discounting, this means that participants with lower SES tended to discount more future rewards. Figure 3.1 illustrates these results for the objective variable: it represents the mean indifference points as a function of time for low-SES participants

and high-SES participants (using a median split). The area under the discounting curve is smaller for low-SES participants, which reflects a steeper discount rate.

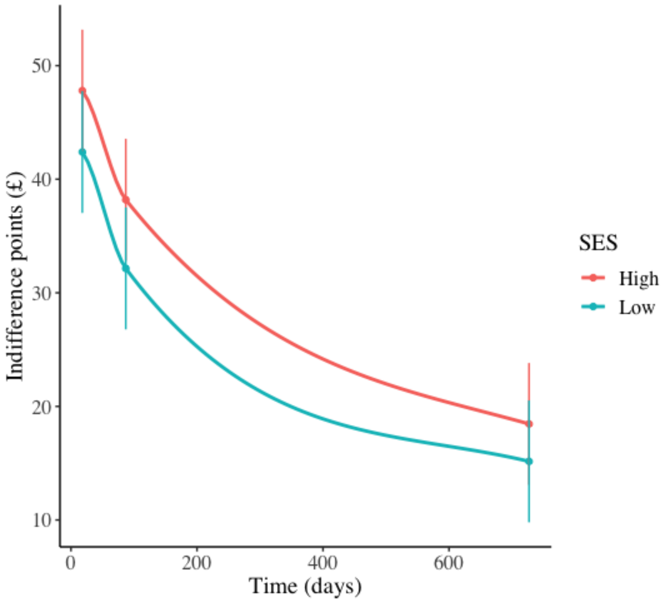


Figure 3.1: Area under the curve of high and low SES participants

This figure displays the mean indifference points as a function of time for high and low SES participants. Three indifference points are plotted on the graph, as the questionnaire contained three different delays. Error bars represent standard error of the mean.

The third step of the mediation analysis was consistent with our hypotheses, as far as pro-environmental attitudes are concerned: the positive association with objective SES disappeared when adding the temporal discounting variable to the regression model (β = 0.07, p = .095, see Table 3.2). We observed a similar pattern with subjective SES: its positive correlation with pro-environmental attitudes disappeared when the discounting variable was added to the model ($\beta = 0.05$, $p = .141$, see Table 3.2), which is compatible with the hypothesis of a mediation. Controlling for gender and age, all of our linear models with SES and environmental variables yielded similar results, indicating that the associations that we observed were not driven by these other variables (see Table 3.A5 in the Appendix).

Size of the mediating effect

To estimate the size of the hypothesized mediating effect and the direct effect, we computed non-parametric bootstrap confidence intervals with the percentile method, using R mediation package (Tingley et al., 2014). Concerning objective SES and pro-environmental attitudes, the average mediating effect was positive and significant ($\beta = 0.031$, $p < .001$) but the direct effect was stronger, albeit still small ($\beta = 0.093$, $p = .040$, see Table 3.3). As could be expected from the regression analyses, we found no significant direct or mediated effect of objective and subjective SES on the behavioural measure using the bootstrap. Finally, the relationship between subjective SES and pro-environmental attitudes was significantly mediated by temporal discounting ($\beta = 0.034$, $p < .001$). There was also a direct effect but it was not significant ($\beta = 0.081$, $p = 0.114$, see Table 3.3).

Discussion

In line with our hypothesis, we find that pro-environmental attitudes are associated both with objective and subjective SES and that this relationship is partially mediated by temporal discounting. However, this result does not translate to the pro-environmental behaviour measure.

Null results concerning this variable could be due either to a gap between attitudes and behaviour, or to certain shortcomings of the donation question that we used to measure behaviour. The low stakes (a donation of 10p) might have contributed to diminish the validity of this measure. It could also be due to some specificities of the answer options we offered: the donation question asked participants to evaluate the importance of an environmental cause with respect to others, which may depend on the participants' evaluations of the other causes as much as the environmental one. It is also possible that the actions we included were too specific or that participants were influenced by the fact that some of the actions could be located in the UK, while

others were relevant for other countries (e.g. "Education in developing countries"). This measure should be modified so as to decide if its validity can be improved.

In addition, a major limitation of studies 1 and 2 is the use of cross-sectional data, with which we cannot establish causal processes definitively. Even though our significant results are encouraging, other causal models could underlie the correlations that were found. Experimental studies are therefore needed before we can claim that there is a causal effect of SES on pro-environmental attitudes which is mediated by temporal discounting.

3.4 Study 3 : An experiment

The goal of this third study is to go beyond correlations and test the causal influence of socioeconomic resources on people's temporal discounting and pro-environmentalism. The only way to act on people's objective SES is to change their income, educational level or occupation, which is obviously difficult in an experimental setting. However, brief psychological interventions such as priming can be used to alter perceptions of one's socioeconomic condition: for instance, Griskevicius et al. (2013) used recession cues to prime their participants with resource scarcity in a laboratory experiment. Another possibility is economic games, which allow experimenters to manipulate participants' perception of their economic resources through income shocks: for example, Haushofer, Schunk and Fehr (2013) found that negative income shocks lead to an increase in temporal discounting, and that positive income shocks weakly decrease discount rates.

Other kinds of research have shown that it is possible to use information about income as an experimental treatment, so as to alter the perception of one's socioeconomic condition (Card et al., 2012; Cruces, Perez-Truglia and Tetaz, 2013; Karadja, Mollerstrom and Seim, 2015; Hvidberg, Kreiner and Stantcheva, 2020; Mijs

and Hoy, 2021). Capitalizing on works demonstrating that faulty beliefs about one's own position in the national income distribution are common (see Norton and Ariely, 2011; Norton et al., 2014; Fehr, Mollerstrom and Perez-Truglia, 2019), economists and psychologists have shown that informing people of their true position in the income distribution can have an impact on political attitudes. For instance, Cruces, Perez-Truglia and Tetaz (2013) found that Argentinian respondents who believed themselves to be relatively richer than they actually were demanded more redistribution, when provided with correct information. Karadja, Mollerstrom and Seim (2015) found that a vast majority of Swedes believed that they were poorer than they actually were relative to others, and that correcting this misperception had an effect on participants' attitudes toward redistribution.

In this study, we use a treatment similar to Karadja, Mollerstrom and Seim's (2015): in order to induce variations in the perception of one's SES, we draw on this work by using an informational treatment, which corrects misperceptions about one's position in the national income distribution. Thus, instead of an income shock in an economic game, we made use of an information shock about relative income. For this experiment, we selected British individuals who believed themselves to be poorer than they actually were (relative to others), and provided them with information about their actual position in the national income distribution. The experiment only targeted participants who held a wrong negative bias about their socioeconomic position in society. For ethical reasons, participants who believed that they were richer than they actually were did not receive any correction.

We reasoned that this positive information shock would be the psychological equivalent of an income shock. Our main hypothesis for this study is that a positive information shock about relative income decreases temporal discounting. As an exploratory hypothesis, we also predicted that the magnitude of the negative bias, and thus the intensity of the treatment, would moderate the effect of the information

shock on temporal discounting (i.e. the bigger the negative bias, the stronger the effect of the treatment), in line with results from Karadja, Mollerstrom and Seim (2015), who found an interaction between the magnitude of the bias and the effect of their treatment. In addition, we made cross-sectional hypotheses concerning the relationships between pro-environmental attitudes and behaviour, temporal discounting and SES, in order to replicate Study 2's results. All theses hypotheses, as well as our methods and analysis plan were pre-registered (https://osf.io/bf8jv).

Materials and Methods

Participants

Participants were recruited via Prolific Academic, relying on pre-screening criteria to filter the participants by nationality and approval rate: only British participants with a minimum approval rate of 90% were recruited. We also excluded students because their reported income may not reflect their actual living standards: students may earn no income but receive parental support. For the power analysis, we used measures of temporal discounting from Study 2. G*Power indicated that 807 participants were needed to be able to detect a minimum effect of 0.2 with a power of 80%. Adding 10% to compensate for attrition, we thus aimed to include at least 888 participants.

910 eligible participants (i.e. with a negative bias) took part in the study. Our pre-registered exclusion criteria were similar to those used in Study 2. We excluded 21 participants who responded too fast (< 500 ms) or too slowly (> 2 minutes) to single question screens, and 16 participants who responded too fast (< 3 s) or too slowly (> 5 minutes) to the other survey pages. 11 participants who failed one or more catch trials in the temporal discounting task were removed from the analyses. In addition, we removed 7 participants who reported a personal monthly income above

£12,500, in order to avoid outliers or potential reporting mistakes. This resulted in a total of 855 participants in the final dataset (52% females), aged between 23 and 74 years (M = 42 years; SD = 10.5). Participants' SES was higher than in the previous study: their average total monthly income was £2,736, ranging from £0 to £12,000 (SD = 1,258, see Table 3.5). Only 2 participants did not finish high school and 80% of them had either completed college or obtained a postgraduate degree.

Procedure

After providing informed consent, participants first answered questions about their SES and demographic characteristics. These answers were then used to calculate whether and by how much participants underestimated or overestimated their relative position in the British income distribution. The survey stopped there for participants who estimated their position accurately or overestimated it (null or positive bias). Those who underestimated their position (negative bias) were randomly assigned to the treatment or control condition. In the treatment condition, participants were presented with a correction of their position in the British society. After this information treatment, the rest of the survey was identical for both groups, where all participants completed the temporal discounting task followed by the environmental attitudes scales. In addition, questions about social trust were added to provide data for another project (Guillou, Grandin and Chevallier, 2020). The measure of pro-environmental behaviour came last. Randomisation checks demonstrated that the two groups were balanced on gender ratio, age, income, educational level, subjective SES and bias (see Table 3.A8 in the Appendix).

Measures

To measure pro-environmental attitudes and temporal discounting, we used the same environmental scales (see Table 3.A1 in the Appendix) and discounting task as in Study 2 (see subsection 3.3). Materials, as well as the data and the R scripts used to analyse the data can also be found in the OSF (`https://osf.io/5sbmr/files/`).

- **Socioeconomic Status**

Concerning SES, we used similar questions as in Study 2, with minor modifications. We computed a composite variable of subjective SES combining the three items from Griskevicius et al. (2013) and participants' response to the MacArthur Scale. We used a slightly modified version of the MacArthur scale focusing on income rather than education and jobs: *"Think of this scale as representing where people stand in the United Kingdom. At the top of the scale (10) are the people who are the best off in terms of overall income. At the bottom (1) are the people who are the worst off in terms of overall income. Where would you place yourself on this scale?"*.

In addition, the survey asked about personal monthly income and benefits, in order to evaluate our participants' actual position in the British income distribution. To decrease reporting error, their annual income was calculated based on reported monthly income and they were then asked to confirm if it corresponded to their actual earnings. As for benefits, we also used a question similar to the one we asked in our previous study, except that participants were asked to specify which amount they received for each type of benefit (jobseeker's allowance, incapacity benefits, etc.). The detailed list of all socioeconomic variables is available in the OSF-folder for this study (`https://osf.io/yztx9/`).

- **Treatment: Information shock**

For all participants, the sum of their reported income and taxable benefits was calculated to determine which decile they belonged to. These calculations were based on statistics from the British government's Personal Income statistics release, which provides percentiles of total annual income (comprising taxable benefits).

This decile was compared to their answer to the MacArthur scale, so as to estimate the extent to which participants had a biased perception of where in the income distribution they were located. We define the bias of a participant as the difference between their perceived and actual income decile. Participants who underestimated their relative income by 1 decile point or more were categorized as having a negative bias. Participants who overestimated their relative income by 1 decile point or more were categorized as having a positive bias. The remaining participants were defined as having no bias. For those who show no bias or a positive bias, the questionnaire came to an end, and only those with a negative bias were randomly assigned to the treatment or control condition. Participants in the treatment condition were presented with a correction of the previous answer they gave, thus receiving a subjective positive income shock, based on their reported income and taxable benefits.

- **Pro-environmental behaviour**

In Study 2, measuring pro-environmental behaviour with a donation question did not yield significant results. In this third study, we used a modified version of the question to improve its validity. Participants were told that we were going to give 10p to a research foundation for every person that participates in our study, and that they could choose the two causes they preferred. We presented them with the following options: *research for climate change mitigation, medical cancer research, research in education sciences, space exploration research, research on Alzheimer disease, or research in economic policies.* We only included causes that are relevant for British participants and we presented the various options in general terms (e.g., climate

change mitigation as opposed to reforestation programmes), in an effort to reduce noise. Answers were transformed into a binary pro-environmental variable (presence of the cause "Research for climate change mitigation" among the two choices = 1, absence = 0). Based on participants' choices, we effectively donated the corresponding amount to relevant organizations afterwards.

Statistical analyses

We used an independent t-test to test our main hypothesis that mean discount rate is different between the control and the treatment groups. The exploratory hypotheses were then tested with regression analyses. To test our hypothesis about the moderating effect of the magnitude of the negative bias, the following pre-registered model was used:

$$DiscountRate = \beta_{10} + \beta_{11}Treatment + \beta_{12}Bias + \beta_{13}Treatment * Bias + \epsilon \quad (3.6)$$

Where *Treatment* corresponds to a binary variable indicating whether a participant is in the control group or the treatment group, *Bias* is a continuous variable referring to the difference between perceived and actual income decile, and *Discount Rate* corresponds to the area under the curve calculated with the discounting task. In addition, following our mediation model we expected that a treatment impacting time preferences would have a downstream effect on pro-environmentalism. Therefore we also predicted a moderated effect of the treatment on pro-environmental attitudes and behaviour:

$$Environmentalism = \beta_{14} + \beta_{15}Treatment + \beta_{16}Bias + \beta_{17}Treatment * Bias + \epsilon \tag{3.7}$$

Finally, since we aimed to replicate our previous findings, we conducted the same cross-sectional analyses as in Study 2. All variables were calculated as in Study 2 and the regression models had the same specifications:

$$Environmentalism = \beta_{10} + \beta_{11}SES + \epsilon \tag{3.8}$$

$$DiscountRate = \beta_{12} + \beta_{13}SES + \epsilon \tag{3.9}$$

$$Environmentalism = \beta_{14} + \beta_{15}SES + \beta_{16}DiscountRate + \epsilon \tag{3.10}$$

The significance of the indirect pathway was again tested with bootstrapping, using R mediation package (Tingley et al., 2014).

Results

Descriptive statistics for key variables are reported in Table 3.5, while Table 3.6 provides the regression estimates for the exploratory models. Figures 3.A1 and 3.A2 in the Appendix display the distribution of bias respectively in the sample of British candidates who were screened for eligibility to the study, and in the final sample of negatively biased participants who were retained (N = 855). As opposed to Karadja, Mollerstrom and Seim's (2015) study in which bias distribution was substantially skewed to the right (indicating that a majority of their Swedish respondents underestimated their position), the distribution in Figure 3.A1 is normal.

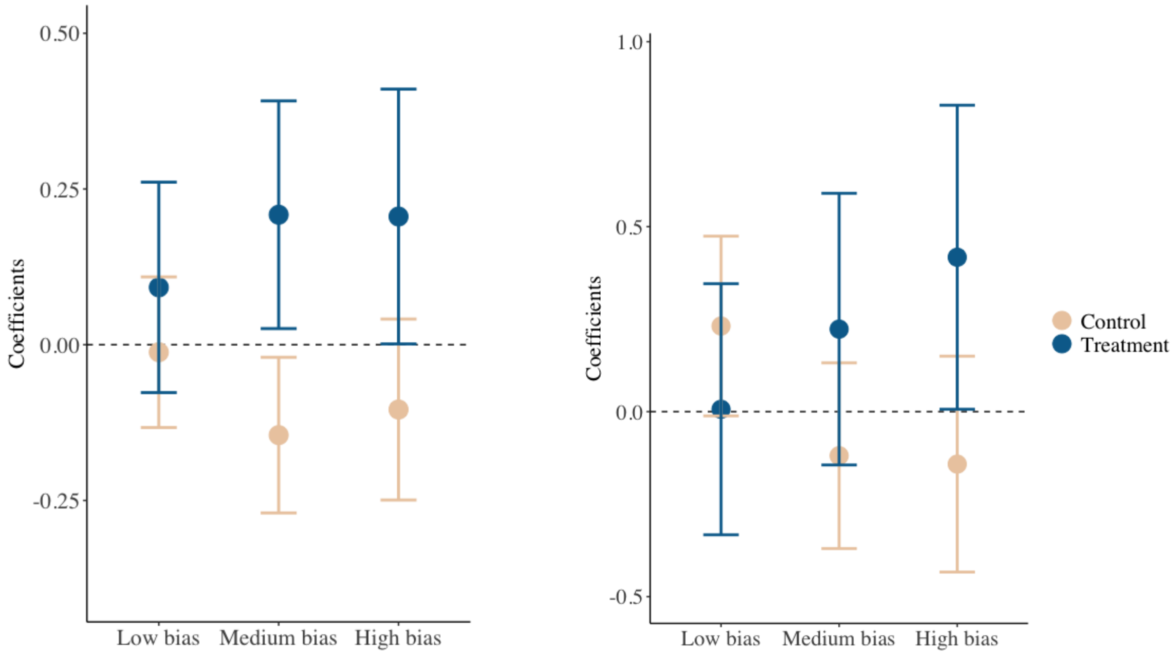
Although this sample is not representative, this suggests that Britons might not underestimate their relative wealth as much as the Swedes. Participants were not homogeneously distributed across the various levels of bias, with a majority displaying a bias lower than 2 (i.e. underestimating their relative income by less than 2 deciles). Therefore, we pooled participants in broader categories: participants who underestimated their relative income by 1 decile were classified as "very low bias", those who underestimated their relative income by 2 were classified as "low bias", those who underestimated their relative income by 3 were classified as "medium bias" and those above 4 were classified as "high bias".

Main and exploratory analyses

Contrary to our hypotheses, the information shock had no impact on temporal discount rates, which were not different in the control group and the treatment group ($t = -0.15938$, $p = .87$); and there was no moderated effect of the treatment on temporal discounting depending on the magnitude of the bias (see Table 3.6).

However, additional analyses revealed that the impact of the treatment on pro-environmental behaviour was affected by the magnitude of the bias: although we observed no main effect of the treatment on pro-environmental behaviour in the full sample ($\beta = 0.02$, $p = .569$), participants in the medium bias and high bias groups responded more to the treatment than participants in the very low bias group (medium bias: $\beta = 0.21$, $p = .026$; high bias: $\beta = 0.21$, $p = .049$, see Table 3.6). Similar results were found for pro-environmental attitudes: participants with a high bias responded more to the treatment than those with a very low bias ($\beta = 0.42$, $p = .047$, see Table 3.6). These interactive effects are represented in Figure 3.2.

Figure 3.2: Interactive effects of the treatment and the magnitude of the bias on pro-environmental attitudes and behaviour



(a) Pro-environmental behaviour (b) Pro-environmental attitudes

Note: These graphs are visual depictions of the interactions between the treatment (information shock concerning relative income) and the magnitude of the bias. The data points represent the coefficients of models 4 and 6 from Table 3.6 and error bars represent 95% confidence intervals. The omitted category is very low bias.

Replication of the correlational mediation model

As was pre-registered, additional mediation analyses were conducted to replicate the correlational mediation model found in the previous study. Following Baron and Kenny's (1986) approach, we replicated the overall patterns found in the previous study (we do not include the detail of these analyses here, but they are available in Tables 3.A6 and 3.A7 in the Appendix). The only discrepancy with Study 2 was that subjective SES was not significantly associated with pro-environmental attitudes (β = 0.01, p = .80).

The analyses based on bootstrapping also yielded very similar results to those

from Study 2: we observed again a positive mediated effect of objective SES on pro-environmental attitudes via temporal discounting ($\beta = 0.012$, $p = .01$), as well as a direct effect ($\beta = 0.085$, $p = .03$, see Table 3.A9 in the Appendix). As in Study 2, we found no significant direct or mediated effect of objective SES on pro-environmental behaviour. The bootstrapping procedure also indicated that the relationship between subjective SES and pro-environmental attitudes was significantly mediated by temporal discounting ($\beta = 0.026$, $p = .01$), while there was no direct effect ($\beta = -0.014$, $p = .77$). One difference with Study 2 was that this time we found a significant mediated association between subjective SES and pro-environmental behaviour ($\beta = 0.010$, $p = .04$).

The fact that, in contrast to Study 2, the mediated association between subjective SES and pro-environmental behaviour became significant in Study 3 can be attributed to changes in the donation question, that were aimed at improving its validity. This seems to bring additional support for our mediation model. However, it should be noted that this can also be attributed to differences in the samples. Study 3 is not a perfect replication of the previous one, as we only retained participants who had a negative perception bias concerning their position in the income distribution. This affected the composition of the sample: in particular, participants in Study 3 have in average higher incomes, educational levels and AUCs than in Study 2 (see Tables 3.4 and 3.5).

Discussion

Prior research has shown that time preferences can shift in response to an experimental shock, for example by exposing participants to positive or negative income shocks in economic games (Haushofer, Schunk and Fehr, 2013), or by using narratives about a sudden change to one's future income (an experimental treatment

also known as episodic future thinking, see Bickel et al., 2016; Sze et al., 2017; Mellis et al., 2018; Liu et al., 2013). In our experiment however, providing participants with positive information about their relative income did not have an effect on temporal discounting. But this treatment had positive interactive effects on environmentalism, such that participants who were the most biased about their relative income responded to the treatment with more positive pro-environmental behaviour and attitudes. The fact that the effects are not mediated by temporal discounting was not anticipated and our data do not allow us to identify the causal channel of change.

One possibility is that, rather than activating considerations about the future, our experimental treatment activated considerations about fairness, which may have had a downstream effect on participants' pro-environmental behaviour. There is a wealth of studies showing that correcting false beliefs about relative socioeconomic position indeed heightens concerns about inequalities (Cruces, Perez-Truglia and Tetaz, 2013; Karadja, Mollerstrom and Seim, 2015; Mijs and Hoy, 2021; Nair, 2018). For instance, a recent large-scale study found that correcting false beliefs about relative socioeconomic position affects attitudes about fairness and redistribution but not other political attitudes (Hvidberg, Kreiner and Stantcheva, 2020). In our study, changes in perceived relative income may have had a specific effect on attitudes about fairness and redistribution, but not on other types of attitudes such as time preferences. This interpretation is well aligned with prior research showing that fairness concerns shape the acceptance of environmental public policies (Sommer, Mattauch and Pahle, 2020), but remains speculatory since we did not measure participants' attitudes about fairness in our study.

In addition, this last study globally replicated the correlational results of the previous study: as in Study 2, we found that the association between SES and pro-environmental attitudes was mediated by temporal discounting. We also observed a mediated effect of subjective SES on pro-environmental behaviour. Thus, Study

3 brings additional support for our mediation hypothesis, although further research with experimental data is needed to ascertain the robustness of this causal model.

3.5 General discussion

The present investigation is related to a vast literature on the relationships between SES and pro-environmental attitudes and behaviour. Relying on psychological theories of poverty, we aimed to gain a better understanding of the mechanisms underlying this relationship. We hypothesized that temporal discounting is one of the factors accounting for socioeconomic differences in pro-environmentalism. Our three studies provide support for this mediation hypothesis. Our results across all studies are compatible with the idea that the correlation between SES and environmental attitudes is partially mediated by time preferences. In Study 3, we found that providing participants with positive information about their relative income had a heterogeneous effect on pro-environmental attitudes and behaviour, but contrary to our hypothesis, the treatment had no impact on temporal discounting.

This research makes several contributions to the literature. First, our studies are the first to test the hypothesis that time preferences mediate the effect of SES on environmentalism. Social scientists have long been interested in the influence of SES on environmental attitudes (Buttel and Flinn, 1978; Diamantopoulos et al., 2003; Harry, Gale and Hendee, 1969), but few studies have explored the psychological mechanisms that underpin this relationship (Eom, Kim and Sherman, 2018*a*).

Second, surveys have often focused on objective markers of SES such as profession, income and education, rather than using self-report scales measuring individuals' subjective experience. Our studies rely on measures of SES that include both subjective and objective indicators. This allowed us to detect that subjective measures are correlated with pro-environmental attitudes in the same way as objective

markers of SES. However, subjective measures appear to have a more consistent effect than income. Results from Study 1 for instance, indicate that education and subjective SES are associated with several types of pro-environmental attitudes, whereas income was correlated positively with pro-environmentalism but not with willingness to increase green taxes and public spending. This is coherent with previous research showing that education is a stronger predictor of pro-environmentalism than income, which can have opposite effects on different types of pro-environmental attitudes (Blankenberg and Alhusen, 2018; Lo, 2016*a*; Pearson et al., 2017; Marquart-Pyatt, 2012). Thus, although the relationship between socio-demographic factors and environmental attitudes has been much studied, Study 1 contributes to the literature on this topic by using more comprehensive measures of SES, while relying on a very large French sample representing a broad range of the population's diversity.

Third, by highlighting the role of time preferences as a potential mediator of the relationship between SES and pro-environmentalism, studies 2 and 3 bring together two streams of research about pro-environmental attitudes and behaviours that have rarely converged into a common approach: one which focuses on socio-demographic determinants and the other on social psychological determinants (Dietz, Stern and Guagnano, 1998).

This potential role of time preferences may be of particular interest for policymakers. Having a better understanding of the factors that drive pro-environmental attitudes and behaviour is indeed crucial for decision-makers who seek to implement environmental policies. A growing literature in psychology has started to address these issues (see Nielsen et al., 2020). For instance, in a recent article, Eom, Kim and Sherman (2018*a*) examined the influence of social class, beliefs in climate change and sense of control on pro-environmental action. Their studies suggest two types of strategies for promoting green behaviour: efforts should focus on changing the beliefs of high SES individuals who do not believe in climate change, and on giving

a greater sense of control to low SES individuals who *do* believe in climate change.

Our mediation model could suggest a similar two-way strategy to promote pro-environmental behaviour, depending on SES: since higher SES individuals tend to be more future-oriented, communication focused on the future costs of unmitigated climate change or biodiversity loss might be more convincing for them than for lower SES individuals. For the latter, highlighting the proximal consequences of environmental issues and bringing them psychologically closer could be more efficient. However, despite this being a frequent suggestion to increase individuals' willingness to act for the environment, empirical research testing this proximizing approach has not consistently revealed the expected positive effects on climate-friendly behaviour so far (Brügger et al., 2015; Spence, Poortinga and Pidgeon, 2012). Mixed results suggest that the effects of proximizing are more complex than is commonly assumed. Further research on how it affects the willingness to act of different segments of the population is needed before large-scale interventions relying on proximizing are implemented.

The experimental results of Study 3 also suggest other directions for future research on the relationship between SES, temporal discounting and environmentalism. Since providing information about *relative* income does not seem to impact discount rates, future research aiming to study the causal impact of SES on time preferences and environmentalism should rather focus on narratives and informational treatments which highlight changes in *absolute* levels of income. For this purpose, the use of episodic future thinking about income shocks, which consists in projecting the self into the future to pre-experience a positive or negative income shock, has proven its efficacy to shift temporal discounting (Bickel et al., 2016; Sze et al., 2017). Similarly, some studies have shown that engaging in episodic future thinking about climate change–related risks and climate change mitigation leads to acting pro-environmentally (Lee et al., 2020; Ho et al., 2020). Future research could

assess whether episodic future thinking about income shocks has a similar effect on pro-environmental behaviour, and whether this effect is partially mediated by temporal discounting.

In addition, the interactive effects of the subjective positive income shock on pro-environmental attitudes and behaviour evidenced in Study 3 suggest new avenues for research and interventions targeting pro-environmental behaviour. Additional surveys are needed to understand the psychological mechanisms behind this observed treatment effect. Since previous research has repeatedly shown that such a treatment has an effect on attitudes about fairness and redistribution, future studies could explore how socioeconomic differences in pro-environmentalism might be related to attitudes about fairness and redistribution.

Future research should also examine the extent to which the results generalize to other countries. Our hypotheses are not country-specific because several multi-country studies have found systematic patterns of relationship between income, pro-environmental attitudes and behaviours on the one hand (Lo, 2016*a*; Marquart-Pyatt, 2012; Pisano and Lubell, 2017) and between temporal discounting and income on the other (Wang, Rieger and Hens, 2016). However, it will be important to validate this model empirically.

There are several limitations to this research, the first being the absence of experimental evidence for our partial mediation model. Thus, different theories about how time preferences relate to pro-environmentalism and SES should be considered. Another possible limitation of our last two studies concerns the measurement of pro-environmental behaviour: unlike environmental attitudes, there is no standardized measure of pro-environmental behaviour for online studies (Lange and Dewitte, 2019). While Study 2 appears to validate our mediation model with respect to environmental attitudes, no significant mediated relationship was found for behaviour. It remains unclear whether we did not find the same results because of an essential difference

between pro-environmental behaviour and attitudes, or because of a lack of validity of our behavioural measure. In Study 2, pro-environmental behaviour measured by a donation to reforestation programmes showed only a low to medium correlation with a validated pro-environmental attitudes scale (Milfont and Duckitt, 2010). Many studies have evidenced a value-action gap in the environmental domain (see Kollmuss and Agyeman, 2002*b*), therefore this discrepancy between attitudes and behaviour does not come as a surprise. However, the magnitude of this discrepancy is surprising, as the correlation is still lower than could be expected. Other considerations related to the alternative donation choices offered to participants may also call into question the validity of the behavioural measure that we used. In Study 3, a transformation of the variable to measure donation to a more global environmental action, and the use of different alternative choices led to a higher correlation with attitudes, which suggests a higher validity of the measure. In addition, there was a mediated effect of subjective SES on pro-environmental behaviour which was similar to that observed for pro-environmental attitudes. But these variations from Study 2 to Study 3 could also be attributed to differences in the samples. Further research could be conducted with other measures of pro-environmental behaviour to test the robustness of our mediation model with respect to behaviour.

Another limitation might be that the individual discount rates inferred from a monetary discounting task cannot be considered as pure measures of time preferences: responses can be influenced by participants' budgetary constraints and the interest rates of the markets to which they have access (see Frederick, Loewenstein and O'donoghue, 2002; Wang, Rieger and Hens, 2016). There has been considerable discussion in the literature as to whether observed socioeconomic differences in temporal discounting actually reflect differences in preferences, or whether they may instead reflect actual or perceived liquidity constraints in conditions of poverty (Haushofer, Schunk and Fehr, 2013). Thus, it would be interesting to see whether

our results replicate using non-monetary rewards in the discounting task, such as environmental gains. However, it is worth noting that according to previous research, individuals discount environmental outcomes in a similar way to monetary outcomes (Hardisty and Weber, 2009).

Finally, it should be emphasized that temporal discounting seem to explain only a small part of the association between SES and pro-environmental attitudes: correlational results from Studies 2 and 3 highlight very small effect sizes, and the mediated effect of objective SES was significantly weaker than the direct effect. Other social psychological factors, such as sense of control, may be stronger mediators of the relationship between SES and pro-environmentalism. Studies which evaluate the relative contribution of different factors would thus be welcome.

Despite its limitations, the present research contributes to a scarce literature that examines the psychological mechanisms underlying the relationship between socio-demographic variables and pro-environmental attitudes and behaviour. Our three studies give weight to the hypothesis that people's preference for the future is a partial mediator of this relationship. Study 3 also shows that information about relative SES impacts pro-environmentalism via other paths. Since having a fine-grain understanding of the antecedents of pro-environmental behaviour can be consequential from an environmental policy perspective, it would be fruitful to continue exploring these lines of research.

3.6 Tables

Table 3.1: Relationships between environmental attitudes and socioeconomic status

	Dependent variable:	
	Pro-environmentalism	Willingness to increase green taxes and spending
	(1)	(2)
Objective SES	0.09***	0.06***
	(0.08,0.11)	(0.04,0.07)
Observations	15,924	15,924
Adjusted R^2	0.01	0.003
RSE (df = 15922)	1.00	1.00
F Statistic (df = 1; 15922)	135.19***	52.96***
Subjective SES	0.07***	0.04***
	(0.05,0.08)	(0.03,0.06)
Intercept	−0.00	0.00
	(-0.02,0.02)	(-0.02,0.02)
Observations	15,924	15,924
Adjusted R^2	0.005	0.002
RSE (df = 15922)	1.00	1.00
F Statistic (df = 1; 15922)	74.31***	31.60***

Note: OLS regression coefficients. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table estimates the association between SES and two environmental outcome variables. *Objective SES* is a composite score combining education and income. *Subjective SES* is a rating of perceived financial ease. *Pro-environmentalism* measures the relative importance of the environment compared to other socio-political issues. *Willingness to increase green taxes and public spending* is a composite score combining participants' willingness to increase public spending for the environment, to fight climate change and to increase taxes on polluting activities. See detailed definitions for each variable in subsection 3.2.

Table 3.2: Baron and Kenny's (1986) three step procedure

	Dependent variable:		
	Pro-environmental attitudes	AUC	Pro-environmental attitudes
	(1)	(2)	(3)
Objective SES	0.09*	0.15***	0.07†
	(0.01,0.16)	(0.08,0.23)	(-0.01,0.14)
AUC			0.14***
			(0.07,0.22)
Observations	650	650	650
Adjusted R^2	0.01	0.02	0.02
RSE	1.00 (df = 648)	0.99 (df = 648)	0.99 (df = 647)
F Statistic	4.99* (df = 1; 648)	15.19*** (df = 1; 648)	9.26*** (df = 2; 647)
Subjective SES	0.08*	0.17***	0.06
	(0.01,0.16)	(0.10,0.25)	(-0.02,0.14)
AUC			0.14***
			(0.07,0.22)
Intercept	0.00	0.00	0.00
	(-0.08,0.08)	(-0.08,0.08)	(-0.08,0.08)
Observations	650	650	650
Adjusted R^2	0.01	0.03	0.02
RSE	1.00 (df = 648)	0.99 (df = 648)	0.99 (df = 647)
F Statistic	4.47* (df = 1; 648)	19.65*** (df = 1; 648)	8.94*** (df = 2; 647)

Note: OLS regressions. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table contains the three regressions of Baron and Kenny's (1986) procedure, aimed at testing the partially mediated effect of SES on pro-environmental attitudes via temporal discounting (AUC). See detailed definitions for each variable in subsection 3.3.

Table 3.3: Correlational mediation analysis based on bootstrapping

	Dependent variable: Pro-environmental attitudes			
Type of SES	Statistic	Estimate	95% CI Lower	95% CI Upper
	Average mediated effect	0.031***	0.012	0.05
Objective	Average direct effect	0.093*	0.002	0.19
	Total effect	0.123*	0.034	0.22
	Proportion mediated	0.249*	0.083	0.89
	Average mediated effect	0.034***	0.013	0.06
Subjective	Average direct effect	0.081	-0.021	0.18
	Total effect	0.115*	0.018	0.22
	Proportion mediated	0.298*	0.084	1.61

	Dependent variable: Pro-environmental behaviour			
Type of SES	Statistic	Estimate	95% CI Lower	95% CI Upper
	Average mediated effect	0.006	−0.002	0.02
Objective	Average direct effect	−0.037	−0.083	0.01
	Total effect	−0.031	−0.077	0.02
	Proportion mediated	−0.194	−2.224	1.43
	Average mediated effect	0.006	−0.002	0.02
Subjective	Average direct effect	−0.018	−0.063	0.03
	Total effect	−0.012	−0.058	0.04
	Proportion mediated	−0.535	−4.555	3.11

Note: correlational mediation analyses testing for the effect of objective and subjective SES on pro-environmental attitudes and behaviour via temporal discounting. Bootstrap-based coefficients and confidence intervals. N = 650. Sampling iterations = 1000. † $p<0.1$; *$p<0.05$; **$p<0.01$; ***$p<0.001$.

Table 3.4: Descriptive statistics

Statistic	N	Mean	SD	Min	Max
Education score	650	3.67	1.07	1	5
Income (£)	650	935	1,187	0	12,000
Benefits (£)	650	113	256	0	1,595
Griskevicius items	650	12.04	3.61	3	21
MacArthur Scale	650	5.43	1.56	1	10
AUC (temporal discounting)	650	19,033	11,497	709	49,276
Activism score	650	4.45	1.11	1	6.8
Conservation score	650	5.17	0.95	2	7
Pro-environmental behaviour	650	0.27	0.45	0	1

Note: *Activism score* and *Conservation score* refer to Milfont and Duckitt's (2010) scales from the Environmental Attitudes Inventory, which were used to calculate participants' pro-environmental attitudes. See detailed definition of each variable in subsection 3.3.

Table 3.5: Descriptive statistics

Statistic (N=855)	Mean	St. Dev.	Min	Max
Education score	4.1	0.9	1	5
Total income (including benefits)	2,736	1,258	1,200	12,000
Griskevicius items	12.7	3.3	3	21
MacArthur Scale	5.2	1.5	1	9
AUC (temporal discounting)	20,501	12,934	709	49,276
Conservation score	5.2	1	1	7
Activism score	4.2	1.2	1	7
Pro-environmental behaviour	0.4	0.5	0	1
Treatment	0.5	0.5	0	1
Bias	-2.2	1.2	-7	-1

Note: Activism score and *Conservation score* refer to Milfont and Duckitt's (2010) scales from the Environmental Attitudes Inventory, which were used to calculate participants' pro-environmental attitudes. See detailed definition of each variable in subsections 3.3 and 3.4.

Table 3.6: Main effect and moderated effect of the treatment on temporal discounting and environmentalism

	Dependent variable:					
	Temporal discounting		Pro-environmental attitudes		Pro-environmental behaviour	
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	−0.01	−0.02	−0.10	−0.22†	0.02	−0.08
	(-0.13,0.14)	(-0.25,0.21)	(-0.24,0.03)	(-0.45,0.01)	(-0.05,0.09)	(-0.20,0.03)
Low Bias	0.05	−0.10	0.22*	0.23†	0.03	−0.01
	(-0.12,0.22)	(-0.35,0.14)	(0.05,0.39)	(-0.01,0.47)	(-0.06,0.11)	(-0.13,0.11)
Medium Bias	−0.04	0.05	−0.02	−0.12	−0.05	−0.15*
	(-0.22,0.15)	(-0.20,0.30)	(-0.20,0.17)	(-0.37,0.13)	(-0.14,0.04)	(-0.27,-0.02)
High Bias	−0.12	−0.08	0.07	−0.14	−0.003	−0.10
	(-0.33,0.08)	(-0.37,0.22)	(-0.14,0.28)	(-0.43,0.15)	(-0.11,0.10)	(-0.25,0.04)
Treatment x Low Bias		0.28		0.01		0.09
		(-0.06,0.62)		(-0.33,0.35)		(-0.08,0.26)
Treatment x Medium Bias		−0.18		0.22		0.21*
		(-0.55,0.19)		(-0.14,0.59)		(0.03,0.39)
Treatment x High Bias		−0.09		0.42*		0.21*
		(-0.50,0.33)		(0.01,0.83)		(0.001,0.41)
Intercept	0.01	0.02	−0.02	0.03	0.43***	0.47***
	(-0.12,0.14)	(-0.13,0.18)	(-0.15,0.11)	(-0.12,0.19)	(0.36,0.49)	(0.40,0.55)
Observations	855	855	855	855	855	855
R^2	0.003	0.01	0.01	0.02	0.003	0.01
Adjusted R^2	-0.001	0.003	0.01	0.01	-0.001	0.003
RSE	1.001 (df = 850)	0.999 (df = 847)	0.996 (df = 850)	0.995 (df = 847)	0.496 (df = 850)	0.495 (df = 847)
F Statistic	0.69 (df = 4; 850)	1.31 (df = 7; 847)	2.52* (df = 4; 850)	2.19* (df = 7; 847)	0.74 (df = 4; 850)	1.38 (df = 7; 847)

Note: OLS regressions. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table estimates the heterogeneous effect of the treatment (subjective positive income shock) depending on the magnitude of participants' bias. The four categories do not have the same number of observations. The omitted category is very low bias.

3.A Appendix

Table 3.A1: Pro-environmental attitudes (studies 2 and 3)

Scale 3. Environmental movement activism

1. If I ever get extra income I will donate some money to an environmental organization
2. I would like to join and actively participate in an environmentalist group.
3. I don't think I would help to raise funds for environmental protection. (R)
4. I would NOT get involved in an environmentalist organization. (R)
5. Environmental protection costs a lot of money. I am prepared to help out in a fund-raising effort.
6. I would not want to donate money to support an environmentalist cause. (R)
7. I would NOT go out of my way to help recycling campaigns. (R)
8. I often try to persuade others that the environment is important.
9. I would like to support an environmental organization.
10. I would never try to persuade others that environmental protection is important. (R)

Scale 8. Personal conservation behaviour

1. I could not be bothered to save water or other natural resources. (R)
2. I make sure that during the winter the heating system in my room is not switched on too high.
3. In my daily life I'm just not interested in trying to conserve water and/or power. (R)
4. Whenever possible, I take a short shower in order to conserve water.
5. I always switch the light off when I don't need it on any more.
6. I drive whenever it suits me, even if it does pollute the atmosphere. (R)
7. In my daily life I try to find ways to conserve water or power.
8. I am NOT the kind of person who makes efforts to conserve natural resources. (R)
9. Whenever possible, I try to save natural resources.
10. Even if public transportation was more efficient than it is, I would prefer to drive my car. (R)

Note: Scales from Milfont and Duckitt's (2010) Environmental Attitudes Inventory. R = reversed coded items.

Table 3.A2: Correlation Matrix (Study 1)

	Gender	Age	Education	Income	Political	Subj. SES	Obj. SES	Spending env.	Spending climate	Tax pollution	Pro-env. Pro-env.
Age	-0.04***										
Education	0.06***	-0.31***									
Income	-0.11***	0.03***	0.22***								
Political position	0	-0.06***	-0.04***	-0.07***							
Subjective SES	-0.05***	0.05***	0.17***	0.43***	-0.07***						
Objective SES	-0.03***	-0.18***	0.78***	0.78***	-0.07***	0.38***					
Spending environment	0.06***	-0.08***	0.08***	-0.02**	-0.03***	0.01	0.03***				
Spending climate	0.04***	-0.04***	0.05***	-0.01	-0.03***	0.03***	0.03**	0.71***			
Tax pollution	-0.02*	0.02**	0.08***	0.04***	-0.06***	0.07***	0.08***	0.35***	0.35***		
Pro-environmentalism	0.03***	-0.09***	0.12***	0.02*	-0.03***	0.07***	0.09***	0.45***	0.41***	0.28***	
Willingness	0.04***	-0.04***	0.09***	0.005	-0.05***	0.04***	0.06***	0.85***	0.85***	0.70***	0.47***

Note: N = 15,924. This table reports Pearson correlations among key variables. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. *Gender* is coded male = 0, female = 1. *Political position* is measured with a question asking participants to indicate where they stand on a scale of 0 to 10, where 0 is left and 10 is right. *Willingness* refers to *Willingness to increase green taxes and public spending*, which is a composite score combining participants' willingness to increase public spending for the environment (*Spending environment*), to fight climate change (*Spending climate*) and their willingness to increase taxes on polluting activities (*Tax pollution*). All environmental items are coded so that the highest scores indicate a pro-environmental position. See subsection 3.2 for a detailed description of the variables.

Table 3.A3: Relationships between environmental attitudes and socioeconomic status (SES), controlling for age, gender and political position (Study 1)

	Dependent variable:	
	Pro-environmentalism	Willingness to increase green taxes and spending
	(1)	(2)
Objective SES	0.08^{***}	0.05^{***}
	(0.06,0.10)	(0.04,0.07)
Age	-0.08^{***}	-0.03^{**}
	(-0.09,-0.06)	(-0.04,-0.01)
Gender	0.05^{**}	0.07^{***}
	(0.02,0.08)	(0.04,0.10)
Political position	-0.21^{***}	-0.26^{***}
	(-0.23,-0.20)	(-0.28,-0.25)
Intercept	-0.08^{**}	-0.10^{***}
	(-0.54,-0.43)	(-0.66,-0.55)
Observations	15,111	15,111
Adjusted R^2	0.06	0.07
RSE (df = 15106)	0.96	0.96
F Statistic (df = 4; 15106)	247.69^{***}	304.58^{***}
Subjective SES	0.07^{***}	0.04^{***}
	(0.05,0.09)	(0.03,0.06)
Age	-0.10^{***}	-0.04^{***}
	(-0.11,-0.08)	(-0.05,-0.02)
Gender	0.05^{**}	0.07^{***}
	(0.02,0.08)	(0.04,0.10)
Political position	-0.21^{***}	-0.26^{***}
	(-0.23,-0.20)	(-0.28,-0.25)
Intercept	-0.08^{**}	-0.10^{***}
	(-0.13,-0.02)	(-0.15,-0.05)
Observations	15,111	15,111
Adjusted R^2	0.06	0.07
RSE (df = 15106)	0.97	0.96
F Statistic (df = 4; 15106)	241.74^{***}	300.72^{***}

Note: OLS regression coefficients. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table estimates the association between socioeconomic status (SES) and two environmental outcome variables, controlling for age, gender and political position. *Gender* is coded male = 0, female = 1. See detailed definitions for each variable in subsection 3.2.

Table 3.A4: Baron and Kenny's (1986) three step procedure (Study 2)

	Dependent variable:		
	Pro-environmental behaviour	AUC	Pro-environmental behaviour
	Logit	*OLS*	*Logit*
	(1)	(2)	(3)
Objective SES	-0.11	0.15^{***}	-0.13
	(-0.29,0.06)	(0.08,0.23)	(-0.31,0.05)
AUC			0.14
			(-0.03,0.31)
Intercept	-0.99^{***}	0.00	-0.99^{***}
	(-1.16,-0.81)	(-0.08,0.08)	(-1.16,-0.82)
Observations	650	650	650
Adjusted R^2		0.02	
Log Likelihood	-379.82		-378.58
Akaike Inf. Crit.	763.64		763.15
RSE		0.99 (df = 648)	
F Statistic		15.19^{***} (df = 1; 648)	
Subjective SES	-0.04	0.17^{***}	-0.07
	(-0.21,0.13)	(0.10,0.25)	(-0.24,0.11)
AUC			0.13
			(-0.04,0.30)
Intercept	-0.98^{***}	0.00	-0.99^{***}
	(-1.16,-0.81)	(-0.08,0.08)	(-1.16,-0.81)
Observations	650	650	650
Adjusted R^2		0.03	
Log Likelihood	-380.49		-379.40
Akaike Inf. Crit.	764.97		764.81
RSE		0.99 (df = 648)	
F Statistic		19.65^{***} (df = 1; 648)	

Note: log odds (Logit) and regression coefficients (OLS). Confidence intervals in parentheses. † $p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. This table contains the three regressions of Baron and Kenny's (1986) procedure, aimed at testing the partially mediated effect of SES on pro-environmental behaviour via temporal discounting (AUC). See detailed definitions for each variable in subsection 3.3.

Table 3.A5: Baron and Kenny's (1986) three step procedure, controlling for age and gender (Study 2)

	Dependent variable:		
	Pro-environmental attitudes	AUC	Pro-environmental attitudes
	(1)	(2)	(3)
Objective SES	0.09*	0.15***	0.06
	(0.01,0.16)	(0.07,0.22)	(-0.01,0.14)
AUC			0.15***
			(0.07,0.23)
Gender	0.20*	−0.08	0.21*
	(0.03,0.36)	(-0.25,0.09)	(0.04,0.38)
Age	−0.02	0.06	−0.03
	(-0.10,0.06)	(-0.02,0.13)	(-0.10,0.05)
Intercept	−0.14	0.06	−0.15*
	(-0.28,0.003)	(-0.08,0.20)	(-0.29,-0.01)
Observations	650	650	650
R^2	0.02	0.03	0.04
Adjusted R^2	0.01	0.02	0.03
RSE	0.99 (df = 646)	0.99 (df = 646)	0.98 (df = 645)
F Statistic	3.42* (df = 3; 646)	6.01*** (df = 3; 646)	6.19*** (df = 4; 645)
Subjective SES	0.08*	0.17***	0.05
	(0.003,0.16)	(0.10,0.25)	(-0.02,0.13)
AUC			0.15***
			(0.07,0.23)
Gender	0.19*	−0.09	0.21*
	(0.03,0.36)	(-0.25,0.08)	(0.04,0.37)
Age	−0.01	0.07	−0.02
	(-0.09,0.07)	(-0.01,0.15)	(-0.10,0.05)
Intercept	−0.14	0.06	−0.15*
	(-0.28,0.005)	(-0.08,0.20)	(-0.29,-0.01)
Observations	650	650	650
R^2	0.01	0.04	0.04
Adjusted R^2	0.01	0.03	0.03
RSE	0.99 (df = 646)	0.98 (df = 646)	0.98 (df = 645)
F Statistic	3.19* (df = 3; 646)	7.85*** (df = 3; 646)	5.99*** (df = 4; 645)

Note: OLS regressions. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table contains the three regressions of Baron and Kenny's (1986) procedure, aimed at testing the partially mediated effect of SES on pro-environmental attitudes via temporal discounting (AUC), while controlling for age and gender. See detailed definitions for each variable in subsection 3.3.

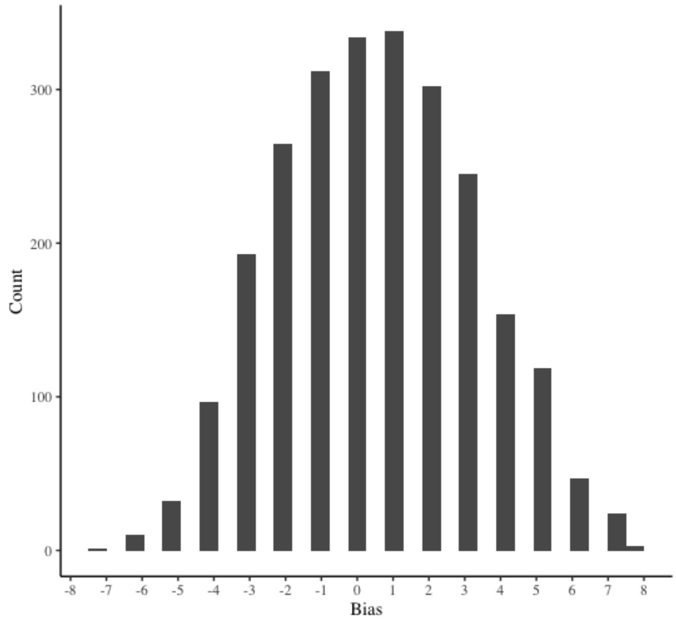


Figure 3.A1: Distribution of bias among potential British participants (Study 3)

Note: This figure displays the distribution of bias among the 3412 potential participants who were screened for eligibility. Bias is defined as the perceived minus the actual decile in the national income distribution. Negative values of bias indicate an underestimation of participant's position in the distribution. Only 910 candidates had a negative bias and were thus eligible to participate in Study 3.

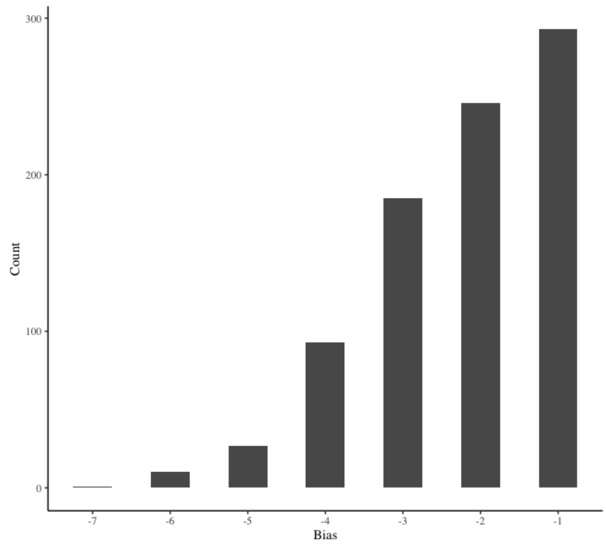


Figure 3.A2: Distribution of bias in the final sample (Study 3)

Note: This figure displays the distribution of bias in the final sample (N = 855). Among the initial candidates, only those with a negative bias concerning their relative position in the the national income distribution were retained to participate to the full experiment.

Table 3.A6: Baron and Kenny's (1986) three step procedure (Study 3)

	Dependent variable:		
	Pro-environmental attitudes	AUC	Pro-environmental attitudes
	(1)	(2)	(3)
Objective SES	0.09**	0.13***	0.08*
	(0.02, 0.16)	(0.07, 0.20)	(0.01, 0.14)
AUC			0.08*
			(0.01, 0.15)
Intercept	−0.00	−0.00	0.00
	(−0.07, 0.07)	(−0.07, 0.07)	(−0.07, 0.07)
Observations	855	855	855
R^2	0.01	0.02	0.01
Adjusted R^2	0.01	0.02	0.01
RSE	1.00 (df = 853)	0.99 (df = 853)	0.99 (df = 852)
F Statistic	6.72** (df = 1; 853)	15.81*** (df = 1; 853)	6.12** (df = 2; 852)
Subjective SES	0.01	0.20***	−0.01
	(−0.06, 0.08)	(0.13, 0.26)	(−0.08, 0.06)
AUC			0.09**
			(0.02, 0.16)
Intercept	−0.00	−0.00	−0.00
	(−0.07, 0.07)	(−0.07, 0.07)	(−0.07, 0.07)
Observations	855	855	855
R^2	0.0001	0.04	0.01
Adjusted R^2	−0.001	0.04	0.01
RSE	1.00 (df = 853)	0.98 (df = 853)	1.00 (df = 852)
F Statistic	0.07 (df = 1; 853)	34.57*** (df = 1; 853)	3.59* (df = 2; 852)

Note: OLS regressions. Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table contains the three regressions of Baron and Kenny's (1986) procedure, aimed at testing the partially mediated effect of socioeconomic status (SES) on pro-environmental attitudes via temporal discounting (AUC). See detailed definitions for each variable in subsection 3.4.

Table 3.A7: Baron and Kenny's (1986) three step procedure (Study 3)

	Dependent variable:		
	Pro-environmental Behaviour	AUC	Pro-environmental Behaviour
	Logit	*OLS*	*Logit*
	(1)	(2)	(3)
Objective SES	−0.06	0.13***	−0.08
	(−0.19, 0.08)	(0.07, 0.20)	(−0.21, 0.06)
AUC			0.13
			(−0.01, 0.27)
Intercept	−0.26***	−0.00	−0.26***
	(−0.40, −0.13)	(−0.07, 0.07)	(−0.40, −0.13)
Observations	855	855	855
Adjusted R^2		0.02	
Log Likelihood	−585.07		−583.37
Akaike Inf. Crit.	1,174.13		1,172.74
RSE		0.99 (df = 853)	
F Statistic		15.81*** (df = 1; 853)	
Subjective SES	−0.11	0.20***	−0.14
	(−0.24, 0.03)	(0.13, 0.26)	(−0.27, 0.004)
AUC			0.15*
			(0.01, 0.28)
Intercept	−0.26***	−0.00	−0.26***
	(−0.40, −0.13)	(−0.07, 0.07)	(−0.40, −0.13)
Observations	855	855	855
Adjusted R^2		0.04	
Log Likelihood	−584.24		−582.12
Akaike Inf. Crit.	1,172.48		1,170.24
RSE		0.98 (df = 853)	
F Statistic		34.57*** (df = 1; 853)	

Note: log odds (Logit) and regression coefficients (OLS). Confidence intervals in parentheses. † p<0.1; *p<0.05; **p<0.01; ***p<0.001. This table contains the three regressions of Baron and Kenny's (1986) procedure, aimed at testing the partially mediated effect of SES on pro-environmental behaviour via temporal discounting (AUC). See detailed definitions for each variable in subsection 3.4.

Table 3.A8: Randomisation checks (Study 3)

	Control group		*Treatment group*			
Statistic	N	Mean	N	Mean	*t*	95% CI
Age	427	42.1	428	41.4	0.993	-0.694, 2.116
Gender	427	0.5	428	0.5	-0.785	-0.094, 0.040
Education score	427	4.1	428	4.1	1.060	-0.058, 0.194
Total income	427	2,701.8	428	2,770.8	-0.802	-237.885, 99.847
Griskevicius score	427	12.7	428	12.7	0.134	-0.417, 0.481
MacArthur Scale	427	5.2	428	5.2	0.094	-0.197, 0.217
Bias	427	2.2	428	2.3	-1.248	-0.263, 0.059

Note: This table reports means for a number of individual characteristics, t statistics and 95% confidence intervals for a test of differences across treatment and control groups. † $p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$. *Bias* corresponds to the perceived minus the actual decile in the national income distribution. *Griskevicius score* is a 3-item scale from Griskevicius et al. (2013) which measures subjective SES. *MacArthur Scale* corresponds to an adaptation of the MacArthur Scale of Subjective Social Status (Adler et al., 2000). See detailed definitions for each variable in subsection 3.4.

Table 3.A9: Correlational mediation analysis based on bootstrapping (Study 3)

	Dependent variable: Pro-environmental attitudes			
Type of SES	Statistic	Estimate	95% CI Lower	95% CI Upper
Objective	Average mediated effect	0.012*	0.001	0.02
	Average direct effect	0.085*	0.004	0.18
	Total effect	0.097*	0.014	0.19
	Proportion mediated	0.123*	0.009	0.62
Subjective	Average mediated effect	0.026**	0.006	0.05
	Average direct effect	−0.014	−0.117	0.08
	Total effect	0.013	−0.091	0.11
	Proportion mediated	2.091	−7.206	7.95

	Dependent variable: Pro-environmental behaviour			
Type of SES	Statistic	Estimate	95% CI Lower	95% CI Upper
Objective	Average mediated effect	0.005 †	−0.0002	0.01
	Average direct effect	−0.020	−0.052	0.02
	Total effect	−0.016	−0.048	0.02
	Proportion mediated	−0.301	−3.283	3.02
Subjective	Average mediated effect	0.010*	0.001	0.02
	Average direct effect	−0.048 †	−0.098	0.00
	Total effect	−0.038	−0.088	0.01
	Proportion mediated	−0.270	−2.62	1.16

Note: correlational mediation analyses testing for the effect of objective and subjective socioeconomic status (SES) on pro-environmental attitudes and behaviour via temporal discounting. Bootstrap-based coefficients and confidence intervals. N = 855. Sampling iterations = 1000. † p<0.1; *p<0.05; **p<0.01; ***p<0.001.

Chapter 4

Does income moderate the effects of green behavioural interventions?

4.1 Introduction

The use of behavioural insights to better inform and design public policy has been increasingly part of the environmental policy debate in many countries (Byerly et al., 2018*a*). Individual consumption and lifestyle choices contribute greatly to climate change (IPCC, 2015), pollution and biodiversity reduction (Foley et al., 2005). Behavioural interventions are often seen as simple and impartial complements (Momsen and Stoerk, 2014) to other more controversial or regressive instruments such as carbon taxation or bans, as they are believed to be "equally applied to all" (Croson, 2014). They leverage cognitive biases that are believed to be universal across human beings, such as the tendency to "follow the herd", to discount rewards in time or to avoid making active decisions (Thaler and Sunstein, 2009).

However, the *degree* to which an individual is susceptible to these cognitive biases varies across different segments of the population. Different ecologies indeed produce different preferences and psychological strategies, and one of the most studied sources

of this heterogeneity is deprivation, often measured by an individual's socioeconomic status (Pepper and Nettle, 2017). For example, a shorter time horizon might lead to higher preferences for the present. Poorer households seem to exhibit more myopic health-damaging behaviours, even when it is more financially constraining, such as in the case of tobacco or alcohol consumption (Pampel, Krueger and Denney, 2010). The impact of behavioural interventions that leverage these biases is therefore likely to differ across income groups in the same society.

Whether low-income households are more or less susceptible to green behavioural interventions is still an open empirical question. Different channels could explain an impact of income level on the effectiveness of behavioural interventions; a mechanical one and a psychological one. On the one hand, it is argued that low-income households are less receptive to non-pecuniary interventions than higher-income households because they face liquidity constraints that restrict their choices and their ability to change behaviour. Roberts (2018) argues that having fewer resources limits the range of choices for a household, making it "nudge-proof" or unlikely to react to a behavioural intervention. It is, for example, easier for a high-income household to recycle more if it is not time constrained, or to switch to a more expensive green consumption if it does not exhibit a strong preference for the cheaper option. On the other hand, beyond the mechanical impact of wealth, it could be argued that low-income households might be more reactive to behavioural interventions than their richer counterparts because they exhibit stronger biases that underlie the effectiveness of these interventions. For example, if low-income households already face a high cognitive load and are more distracted because their minds are busy struggling to make ends meet (Mani et al., 2013*b*; Shah, Mullainathan and Shafir, 2012), then they might be more likely to be affected by a choice architecture that leverages procrastination or distraction, such as making green electricity the default energy option.

In this review, we focus on this second channel; the psychological mechanisms underlying the effectiveness of behavioural interventions. We examine how they differ across income groups and thus are likely to affect the relative effectiveness of behavioural interventions. We review the literature taking the example of three of the most utilised interventions in environmental behavioural public policy: defaults, commitment devices and social norm messaging.

4.2 Heterogeneous biases, heterogeneous nudges?

Defaults

Default interventions consist in setting the policy maker's desired option as the one that consumers receive if they do not actively request another one. Their high effectiveness and ease of execution makes them attractive to policy makers wishing to influence choice without limiting it (Jachimowicz et al., 2019). Primarily, defaults were successfully implemented to increase pension saving (Choi et al., 2002) and organ donations (Johnson and Goldstein, 2003*a*). In the environmental policy context, there is convincing empirical evidence of the power of "green" defaults in increasing energy and resource conservation (Ebeling and Berger, 2015; Pichert and Katsikopoulos, 2008). In a Swedish University, switching the printers' default settings from simple to double-sided led to an immediate and long-term reduction of 15% in daily paper consumption, while merely informing and encouraging users of the environmental benefits resulted in no change in behaviour (Egebark and Ekström, 2016). Default interventions have also been identified as a promising tool for increasing take-up of green energy. Pichert and Katsikopoulos (2008) show that pre-setting "green" electricity as the default option increased its adoption by households. Similarly, in two recent large scale experiments involving 200,000 households and 8,0000 companies in Switzerland, Liebe, Gewinner and Diekmann (2021) found that setting the renewable

energy option as the pre-determined option led to an 80% increase in the rate of adoption, an effect that lasts at least 4 years.

A number of cognitive factors explain their effectiveness. Firstly, a vast literature in behavioural economics and psychology has demonstrated that individuals exhibit status quo bias, or a tendency to stay in the existing state when faced with a choice. This is true even when there is no evidence suggesting the status quo is better than the alternatives (Samuelson and Zeckhauser, 1988; Thaler and Benartzi, 2004), and when the status quo is clearly worse, such as in the case of a fraudulent default subscription programme (Letzler et al., 2017). This bias is linked to a propensity of individuals to be risk and loss averse, meaning they tend to avoid risk and weigh losses more heavily than gains (Tversky and Kahneman, 1992). Individuals are, as such, more dissatisfied by a bad outcome when it is a consequence of their actions, than by an equally bad outcome resulting from inaction (Kahneman and Tversky, 2013). This might lead individuals to prefer to stay in their current position to avoid risking loss. Secondly, the default option spares people from time and cognitive costs associated with active decision making. Indeed, active choice towards a preferred alternative entails mobilizing resources to gather information about available alternatives in order to make an informed decision. Sticking with the pre-determined choice simplifies the decision maker's task, especially in the presence of bounded rationality or imperfect information (Thaler and Benartzi, 2004). Finally, individuals may stick with the default because it suggests an implicit recommendation by an authority or an expert towards the most appropriate or socially preferred choice (Madrian and Shea, 2001; Choi et al., 2003; Johnson and Goldstein, 2003*b*).

Low-income households are likely to experience higher levels of status quo bias, less information and a higher adherence to social norms. Firstly, low-income households display higher levels of risk and loss aversion. When faced with resource scarcity, higher uncertainty, and an inability to shift risk to a third party, the costs of

bad outcomes are higher. This causal link has been identified using exogeneity in rainfall and windfall as instruments to demonstrate that lower levels of income lead to higher risk (Guiso, Einaudi and Paiella, 2003) and loss aversion (?Tanaka, Camerer and Nguyen, 2010*b*), measured using hypothetical economic questions from household surveys. Haushofer and Fehr (2014) points out that poverty often leads to negative affect and stress (Chemin, de Laat and Haushofer, 2013), which in turn causes higher levels of risk aversion (Cohn et al., 2015). Accordingly, lower-income households, exhibiting higher loss and risk aversion are going to be more reluctant to opt-out of the status quo (Bekir and Doss, 2020). Additionally, low-income individuals face relatively higher cognitive load than high-income individuals (Mani et al., 2013*b*). Secondly, lower income households might have less information about their alternatives than their higher income counterparts (Bertrand, Mullainathan and Shafir, 2006) or might find it more costly to mobilize cognitive and time resources to gather information in order to make an active choice (Shah, Mullainathan and Shafir, 2012). Ghesla, Grieder and Schubert (2020) find that people who are uninformed about the choice, who deem the choice as complex and who perceive the default as a recommendation are less likely to opt out of the default. In parallel, an experiment targeting environmental economists at a conference concluded that the effect of a green default option is weakened when subjects have high experience or knowledge about the topic in question (Löfgren et al., 2009).
Finally, if the default option is perceived as the implied recommendation of an expert or as the socially acceptable option, lower levels of self-confidence (Whitehead et al., 2016), information and a higher adherence to social norms (Jacquet et al., 2019, 2018; Stephens, Markus and Townsend, 2007) might lead low-income households to have a greater willingness to accept the implicit endorsement.

Recent evidence confirms that low-income households are indeed more likely to stick to default options than high-income households. This has been mostly

documented in articles examining savings plan defaults such as 401(k) (Madrian and Shea, 2001; Choi et al., 2003). This is not explained by default options coinciding with the preferences of low-income households. Beshears and Choi (2012) find similar results when studying heterogeneous responsiveness to defaults, even when taking into account the individual preferences of contribution. Similarly, Letzler et al. (2017) use a natural experiment whereby a government lawsuit led to the automatic cancellation of a fraudulent subscription programme for some consumers, while others had to cancel it actively. They find that the rate of default cancellation was 63 percentage points higher than that of active cancellation, even when the customers were informed. Heterogeneous effects show that households in less affluent neighbourhoods were less likely to actively cancel their subscription. Hortaçsu, Madanizadeh and Puller (2017) also show that people in lower socio-economic status neighbourhoods are less likely to switch away from their existing electricity suppliers to cheaper entrants offering nearly identical products.

A small number of studies look at the heterogeneous impact of defaults across socio-economic groups in the environmental policy context. In a recent study, Ghesla, Grieder and Schubert (2020) find that poorer households are more susceptible to the power of "green defaults" and are less likely to move away from subscription to more environmentally sustainable. Conversely,

Goal setting and commitment devices

Goal setting or commitment devices refer to interventions that give the possibility for individuals to make promises in the present about actions they wish to accomplish in the future, in the form of oral or written pledges. These type of interventions have been documented as successful economic (Bauer, Chytilová and Morduch, 2012) context such as microfinance and retirement savings (Ashraf, Karlan and Yin, 2010; Madrian and Shea, 2001) and have shown very promising results in encouraging

conservation behavior (Abrahamse et al., 2007*b*; Andor and Fels, 2018*a*; Byerly et al., 2018*b*; Jaeger and Schultz, 2017; Schultz et al., 2013). For example, an intervention prompting US households to set an energy reduction goal on an online platform and sending them reminders was successful in significantly reducing electricity usage by 8% in the short run and 4.4% in the long-run (Harding and Hsiaw, 2014). McCalley and Midden (2002) compared the effect of self-set and assigned goals in decreasing energy use and found that both goal groups reduced their use by 21% and 19%, respectively. The success of the intervention was not dependent on the expected monetary savings. The literature suggests that these type of interventions aim at counteracting the cognitive tendency termed present bias, or the well-documented inclination of people to discount their future preferences in favor of more immediate gratification, i.e. people more often prefer smaller, earlier over larger, more delayed benefits (Thaler and Shefrin, 1981). Interventions that encourage people to informally commit to a future consumption goal can thus counteract or reduce this bias by making future benefits more salient in the present and by increasing the short term cost of not accomplishing a predetermined goal. Because time preferences imply trade-offs between one's present and future self, the concept is particularly relevant when considering pro-environmental action, a context that suffers from a significant temporal trade-off.

Present bias, sometimes measured by time discounting rates, differs across households and individuals (Harrison, Lau and Williams, 2002*b*) and one of the possible determinants of this heterogeneity is wealth. Low-income households reveal greater future discounting compared to richer people, i.e. they have more myopic preferences. These findings are consistent around the globe with researchers finding the same correlation in studies conducted in the US, Ethiopia, India and Denmark (Harrison, Lau and Williams, 2002*b*; Lawrance, 1991*b*; Pender, 1996; Yesuf and Bluffstone, 2008). While present orientation can cause households to invest less

and take on lower paid jobs, scarcity itself is believed to increase impulsivity and present bias. In fact, lower income is attributed to higher levels of uncertainty and shorter time horizons, which makes waiting for long term rewards more risky (Pepper Nettle, 2017). Moreover, the urgency of present necessities and the circumstances that financially constrained households usually face, such as the absence of credit markets or lead to myopic preferences, regardless of underlying intrinsic cognitive biases. Studies using experimental and quasi-experimental settings confirmed the causal impact of income variation on time discounting; using rainfall as an instrumental variable for income in Vietnam (Tanaka, Camerer and Nguyen, 2010*b*) and Ethiopia (Di Falco et al., 2019*b*), an exogenous income shock resulting from a natural disaster in Thailand (Cassar, Healy and von Kessler, 2017*b*) and a laboratory manipulation of income levels, researchers show that negative income shocks result in higher discounting (Haushofer and Fehr, 2013).

If lower-income households systematically exhibit higher future discounting, then we might expect that behavioural interventions aiming at counteracting the present bias, such as goal setting or commitment devices, will be more effective in shifting behaviour in these households. Insights on the effectiveness of microfinance and health policy confirms that these interventions work best on individuals with higher myopic tendencies. Ashraf, Karlan and Yin (2010) examine heterogeneous effects of commitment saving products and find that they were more accepted by individuals with high time discounting. In Uganda, Grohmann, Lakemann and Seitz (2020) found saving goals had no average effect on savings, but only present-biased individuals saved more. Similarly, Savani (2019) suggests that people with more short-termist attitudes are also the ones who benefitted the most from health commitment devices. In education policy, Castleman and Page (2017) show that planning prompts and reminders to students were successful in increasing outreach, but that these effects were mostly concentrated in the low-income subgroup. The intervention made salient

near-term deadlines and provided students with a way to commit to a given task in the moment, the messages can prompt students to focus on completing required tasks rather than putting them off. The evidence for this claim is lacking in the literature on commitment and goal setting in the environmental literature. In Germany, Löschel, Rodemeier and Werthschulte (2020) found that commitment goal setting using mobile phones had no effect on energy consumption targets in a high-income sample showing no present-bias tendencies.

Social influence

Directly observing how the majority of people behave, or indirectly being communicated this information is highly influential on one's own behaviour (Nolan et al., 2008). Empirical work has confirmed that humans have a tendency to mimic peers in a variety of fields. Therefore, interventions that draw attention to the social norm have been extensively used to promote pro-environmental behaviour, such as energy and water conservation (Allcott and Mullainathan, 2010; De Dominicis et al., 2019; Ferraro and Price, 2013), recycling (Schultz, 1999), sustainable consumption (Demarque et al., 2015; Einhorn, 2020; Melnyk et al., 2011), towel reuse (Goldstein, Cialdini and Griskevicius, 2008) and commuting (Kormos, Gifford and Brown, 2015). In one of the largest randomized experiments in the field Allcott (2011) measures the impact of social influence on energy conservation. The intervention, which consisted in sending households their energy usage and how it compares to neighbours, was successful in decreasing energy usage by the same amount expected with a 10% price increase. This level of tailoring or personalization is not necessary for the effectiveness of social norm interventions. Simply pointing out the generic local social norm could be sufficient in altering behaviour. For example descriptive social norm messages such as the one tested by Nolan et al. (2008) "77% of San Marcos residents often use fans instead of air conditioning to keep cool in the summer!" had the

strongest effect on participants' energy conservation out of four different informational messages. Outside experimental settings, (Bollinger and Gillingham, 2012) show that a household is more likely to adopt solar panels the more visible a peer's installation of a photovoltaic solar panel is.

Interventions based on social norms rely on human's inclination to "follow the herd". Conformist behaviours could be a deliberate strategy for fitting in, maintaining good bonds and using learning from others. The information people acquire by observing peers could be seen as a signal of desired, "proper" or socially acceptable behaviour by the group (Bernheim, 1994) and deviations from these social customs could be punished by loss of "reputation" (Akerlof et al., 2015) or because the individual assumes that others have better information (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992).

Not all groups are equally susceptible to social influence (Savani, 2019) and low-income individuals tend to prioritize choices that are aligned with social norms. This tendency can be construed as a consequence of the fact that poorer people belong to more interdependent social networks because of their social and material conditions (Stephens, Markus and Townsend, 2007). From an evolutionary perspective, relying on this social information allows an individual to benefit from actions previously tested out and is a strategy to decrease short-run environmental risks. Therefore the more risky the environment is perceived to be, the greater people's susceptibility to social influence should be (Forss, Koski and Schaik, 2017; Jacquet et al., 2019, 2018; Rieucau and Giraldeau, 2011). In line with this hypothesis, Jacquet et al. (2019) found that the more harsh and unpredictable a participant's childhood was, the more they were susceptible to social influence when making a moral judgement of unknown faces. Similarly, it was shown that individuals with a lower socio-economic background are more likely to make choices that are similar to others, to display more positive feelings when other participants make the same choices as them (Stephens,

Markus and Townsend, 2007) and to even change an original choice to better align with others (Na et al., 2016). Targeting pro-environmental behaviour, Eom, Kim and Sherman (2018*b*) find that the perceived descriptive norm about pro-environmental behaviour is a predictor of the likelihood of donating to an environmental cause, but that this relationship is true only among participants coming from a low socio-economic background.

Based on these findings, we expect individuals from lower socio-economic backgrounds to be more strongly influenced by social norms interventions than their wealthier peers. In two large experiments in Sacramento, Ayres, Raseman and Shih (2009) finds that households in the lowest quintiles of wealth decreased electricity and gas consumption more than households in the highest quantiles following the reception of peer feedback reports. However, the bulk of the evidence points in the opposite direction and shows that providing tailored comparative feedback is more effective among wealthier households (Brick, DeMartino and Visser, 2017; Ferraro and Price, 2013; Nolan et al., 2008; Schultz et al., 2007*b*). These observations could be due to the fact that wealthier households are also the highest-users of energy at baseline (Brent et al., 2020), and thus have a bigger margin of improvement and are "more intensely treated" by the social comparison interventions (Chen and Qin, 2020). While most of the literature is based on experiments in the United States, Andor and Fels (2018*a*) finds no effect of social comparison in a Germany wealthy sample with initial low energy usage. It would be useful to examine social norm interventions that do not depend on the baseline behaviour of the household, such as communicating a generic descriptive norm. To our knowledge, interventions evoking a generic social norm have generally not examined heterogeneous effects of the intervention across income groups.

4.3 Fairness and distributional concerns

Regardless of the vigorous, continued discussion around the ethics of green nudges, such as autonomy and transparency, very few challenge distributional implications and examine it empirically. When interventions systematically impact some segments of society more than others, fairness and distributional issues must be considered. From a fairness perspective, a behavioural intervention that predominantly helps the most vulnerable households reach welfare-enhancing goals would decrease disparities, such as in the case of smoking cessation (Lee et al., 2013) and retirement savings (Beshears and Choi, 2012). In the environmental context, policy-makers aim to maximize society's welfare by incentivizing behaviours that might incur monetary costs to households. In the case of green behavioural interventions that incentivize choices entailing cheaper or less frequent consumption, such as water and energy conservation (Allcott, 2011; Ferraro and Price, 2013) or public commuting (Kormos, Gifford and Brown, 2015), monetary and environmental goals are aligned, such that households for whom the intervention is effective end up polluting less and spending less. However, many environmental policies motivate a choice or a behaviour with higher monetary costs to households, such as the consumption of green labelled products (Demarque et al., 2015; Melnyk et al., 2011), the adoption of green energy, CO2 offsetting (Tyers, 2018) or increased donation to environmental charity (Crow, Mathmann and Greer, 2019; Nielsen et al., 2017; Agerström et al., 2016; Bartke et al., 2017). Here, distributional concerns might be relevant. For example, in an online shopping setting, Demarque et al. (2015) points out that participants for whom the social norm nudge was effective in buying green labelled products spent more, considering that green products are generally more expensive. In the case of defaults, setting the default on a green and expensive option, could entail negative distributional consequences since renewable energy is often more costly compared with conventional ones using fossil fuel (Sundt and Rehdanz, 2015). Ghesla, Grieder and

Schubert (2020) were one of the very few to directly study this. Using experimental evidence and a four-year follow-up, they found that not only poorer households were more likely to stick with the more expensive greener energy option, but that they were more likely to prefer the cheaper, less environmentally friendly option, which means that they were de facto exposed to a greater preference mismatch. In fact, low-income households are also less willing to pay or act for the environment (Guerin, Crete and Mercier, 2001*b*; Kennedy and Givens, 2019). For example, the willingness to pay for green electricity also increases with income (Zorić and Hrovatin, 2012). Even though this is partly because it might involve costly behaviour, engagement in pro-environmental behaviour is also influenced by psychological factors associated with socioeconomic background. For example, given the temporal nature of environmental issues, low-income households' myopic preference and immediate life necessities may have a negative effect on their willingness to engage in environmental action that entails future benefits. Research around the globe confirms that pro-environmental attitudes are less widespread among lower socioeconomic status individuals, even though they are more worried about the risks associated with environmental hazards (Franzen and Meyer, 2010; Lo, 2016*b*; Marquart-Pyatt, 2008).

4.4 Conclusion

Lower income has been associated with higher levels of status quo bias, time discounting and social conformity. This suggests that behavioural interventions that exploit or counteract these biases must be more effective in changing the behaviour of low-income compared to high income households. Previous research has been predominantly dedicated to estimating the total effect across all segments of society and there remains a gap in the literature on the heterogeneous impacts of green behavioural interventions among different income groups and how that might affect a

policy's fairness. While default options and tailored social comparison interventions have received more distributional concern and investigation, heterogeneous effects of commitment devices and generic social norm messaging has been largely ignored. Particularly in situations where the desired behaviour is costly to households, ignoring the heterogeneity of the degree of cognitive biases might lead already disadvantaged segments of the population, who typically pollute less (Piketty and Chancel, 2015), to disproportionately bear the consequences of green behavioural policies.

Essais sur l'application des connaissances comportementales aux politiques environnementales

Résumé

Les êtres humains façonnent l'environnement qui les entoure. Nous extrayons de l'eau pour la boire, nous abattons des forêts pour nous nourrir et nous chauffer, nous rejetons des polluants atmosphériques pour nous déplacer et nous jetons indûment des cigarettes et des déchets plastiques dans la nature. La croissance rapide de la population, de l'économie et de la mondialisation a entraîné une augmentation de la demande de ressources et de la production de pollution et d'émissions de gaz à effet de serre à un rythme très élevé et non soutenable à long terme, affectant de manière dramatique des écosystèmes entiers et réchauffant dangereusement la planète. Des études récentes estiment que 75% des terres émergées et 66% des océans ont été profondément modifiés par l'activité humaine, menaçant d'extinction plus d'espèces que jamais auparavant. Les conséquences du changement climatique d'origine humaine sur les humains eux-mêmes, comme les conditions météorologiques extrêmes et la destruction des moyens de subsistance, pèsent principalement sur des populations déjà défavorisées. En 2019, les aléas climatiques ont engendré 24,9 millions de réfugiés dans plus de 140 pays, touchant de manière disproportionnée les plus vulnérables (Brondizio et al., 2019). Ces conséquences devraient s'aggraver à mesure que la taille et la richesse de la population mondiale continuent de croître, et malgré les efforts récents pour inverser ces tendances, nous ne sommes pas sur la bonne voie. Au rythme actuel des émissions de dioxyde de carbone, la température de la planète devrait augmenter de 3 à 5 degrés Celsius d'ici à la fin du siècle, soit bien plus que les 2 degrés Celsius visés par la communauté internationale pour éviter des événements catastrophiques. Le plan présenté dans le récent rapport du groupe d'experts intergouvernemental sur l'évolution du climat ainsi que les modèles projetant des scénarios alternatifs pour limiter les températures mondiales attirent l'attention sur le rôle indispensable des changements de mode de vie et de comportement, tels que la réduction des régimes carnés, du chauffage, de la climatisation des ménages et des transports individuels (Van Vuuren et al.,

2018). Ainsi, même si des changements structurels sont nécessaires, il est désormais largement admis que la modification des comportements individuels est essentielle pour relever les défis environnementaux.

La compréhension de la psychologie humaine nous aide à comprendre pourquoi les humains endommagent la nature. Des facteurs psychologiques mais aussi structurels, économiques et politiques expliquent pourquoi il est courant que les humains détériorent l'environnement qui assure leur survie et pourquoi il a été difficile d'inverser ce schéma malgré une prise de conscience croissante. La théorie économique suggère quant à elle que, face aux externalités et aux propriétés de bien public liées aux questions environnementales - telles que l'absence de droits de propriété et de prix du marché - les marchés ne parviennent pas à réguler l'exploitation de l'environnement. Ainsi, bien souvent, le problème de la maximisation du bien-être des individus ne coïncide souvent pas avec celui de la société. La recherche en psychologie environnementale met en lumière d'autres barrières psychologiques potentielles au comportement respectueux de l'environnement, même en présence d'une information parfaite et d'une volonté de protéger la planète. L'une des principales caractéristiques des questions environnementales est l'asymétrie des avantages et des coûts ; les avantages de la consommation des ressources sont très palpables, immédiats et se produisent à un niveau local. Les coûts, en revanche, sont souvent invisibles, se produisent dans un avenir lointain et sont éloignés géographiquement. En parallèle, les êtres humains ont développé des biais cognitifs au cours des années d'évolution - tels que le biais de saillance, le biais pour le présent et le biais d'optimisme - qui pourraient les amener à faire un choix sous-optimal pour eux-mêmes ou pour la société aujourd'hui lorsqu'ils sont confrontés à ces asymétries. Par exemple, le biais de saillance décrit notre tendance à privilégier les éléments saillants et visibles du processus de décision. C'est pourquoi, les aspects vifs et tangibles de la consommation d'un bon hamburger, comme son goût, éclipsent facilement ses coûts

environnementaux associés, épars et difficiles à mesurer, comme la déforestation de la forêt amazonienne, la production de méthane par les vaches et l'utilisation de grandes quantités d'eau. Le biais pour le présent est une autre barrière psychologique connexe qui peut faire obstacle à un comportement pro-environnemental. En effet, nous préférons souvent les récompenses immédiates aux récompenses futures. Ainsi, nous actualisons les bénéfices futurs à un taux très élevé et nous surpondérons les considérations à court terme (Loewenstein and Prelec, 1992). Nous observons que les individus agissent de la sorte lorsqu'ils prennent des décisions en matière de santé et d'économie, mais ce phénomène est particulièrement pertinent dans le contexte environnemental, qui fait l'objet d'importants arbitrages intertemporels. Réduire les émissions individuelles de carbone en limitant l'utilisation de la voiture implique une certaine retenue dans le présent, afin de maintenir des conditions de vie décentes pour les générations futures ou pour soi-même dans le futur. Enfin, nous pouvons avoir de forts biais liés à l'assimilation des informations. Le biais d'optimisme, par exemple, nous amène à croire que, par rapport aux autres, nous avons moins de chances de subir un mauvais résultat et plus de chances d'obtenir un résultat positif. Cela nous pousse à sous-estimer les risques individuels réels des risques environnementaux, tels que les ouragans et les sécheresses, même lorsqu'ils nous sont communiqués de manière efficace. Par conséquent, les réponses politiques à un problème aussi complexe nécessitent un mélange d'outils politiques inspirés de différentes disciplines, et l'étude du comportement humain en est un élément central.

Comprendre la psychologie humaine peut également aider à élaborer des politiques plus efficace pour contrer cet échec individuel et collectif à prendre des mesures pro-environnementales. En effet, les gens réagissent non seulement aux incitations, à l'information et à la persuasion, mais aussi à la manière dont ces interventions sont conçues, encadrées et communiquées (Kahneman, 2011). Plus précisément, la

recherche en psychologie environnementale est utile pour comprendre l'impact et l'acceptabilité des interventions économiques traditionnelles, telles que les taxes et les subventions (McCaffery and Baron, 2006; Finkelstein, 2009). Il a par exemple été suggéré que les individus pourraient être beaucoup plus disposés à payer pour une redevance de compensation écologique lorsqu'elle est appelée "compensation carbone" plutôt que "taxe carbone", en particulier s'ils s'identifient comme républicains ou indépendants sur le spectre politique américain (Hardisty, Johnson and Weber, 2010). Les outils de provision d'informations pourraient également être mieux adaptés pour combler le fossé persistant entre la connaissance et l'action en matière d'environnement. Les méta-analyses révèlent une grande hétérogénéité dans l'efficacité de la provision d'informations (Andor and Fels, 2018*b*; Karlin, Zinger and Ford, 2015), ce qui suggère que le contenu et le format des informations comptent pour beaucoup dans leur efficacité. Par exemple, il est prouvé que les incitations informationnelles sont plus efficaces lorsqu'elle soulignent les pertes potentielles plutôt que les gains (Ghesla et al., 2020). D'autres interventions non monétaires, telles que l'apport d'un retour d'information à haute fréquence par le biais de compteurs d'électricité et d'eau, ont été mises en place pour surmonter le biais de saillance et le biais pour le présent auquels sont confrontées les décisions de consommation de ressources. Ces interventions ont pour objectif daugmenter la saillance des coûts environnementaux dans le présent. Le fait de fournir aux gens leur profil de consommation d'eau en temps réel pendant qu'ils se douchent a permis de réduire la consommation d'eau de 11 % dans les chambres d'hôtel et de 22 % à la maison (Tiefenbeck et al., 2018, 2019). Une autre contribution bien documentée aux incitations environnementales concerne l'importance des normes sociales lors de la prise de décisions. Nous savons que les humains ont tendance à imiter les autres ; les ménages sont plus susceptibles de s'équiper de panneaux photovoltaïques si leurs voisins le font (Bollinger and Gillingham, 2012) et les individus sont plus susceptibles

de jeter des déchets dans des environnements où des personnes en ont déjà jeté (Keizer, Lindenberg and Steg, 2008). Cela a inspiré un grand nombre d'interventions comportementales basées sur la comparaison sociale qui se sont avérées efficaces pour encourager la conservation des ressources, parfois équivalentes à des augmentations importantes des prix (Ferraro and Price, 2013; Allcott, 2011). Enfin, la psychologie environnementale peut aider à anticiper ou à éviter les effets de retour de certaines mesures d'atténuation. Par exemple, nous savons maintenant que les incitations au recyclage devraient s'accompagner d'incitations à consommer moins, car les gens ont tendance à produire beaucoup plus de déchets lorsque la possibilité de recyclage atténue une partie de la culpabilité associée à l'usage (Catlin and Wang, 2013).

La première partie de cette thèse contribue à cette littérature en apportant de nouvelles démonstrations de l'efficacité des connaissances comportementales pour réduire la pollution. Le chapitre 1 explore les méthodes psychométriques utilisées en psychologie pour informer la politique de lutte contre les déchets urbains depuis le laboratoire. Le chapitre 2 fournit des preuves de terrain sur la façon dont l'augmentation de la saillance de la pollution par le biais de compteurs intelligents et de la comparaison sociale pourrait être plus efficace que la fourniture d'informations génériques pour réduire le comportement polluant des ménages.

Chapitre 1 : Informer la politique contre les déchets sauvages au laboratoire

Les déchets sauvages constituent un défi important pour les autorités locales et le maintien d'un environnement public propre est souvent considéré comme une priorité absolue par les habitants. Cela engendre une pression sur les municipalités pour qu'elles augmentent les budgets annuels déjà importants consacrés au nettoyage, et pour qu'elles maximisent l'efficacité des stratégies déjà en place pour prévenir

les comportements d'abandon de déchets. L'une des options dont disposent les autorités est d'augmenter le nombre de poubelles dans l'espace urbain, un facteur qui s'est avéré réduire la probabilité d'une élimination inappropriée des déchets. Une autre solution consiste à accroître la visibilité des poubelles existantes. Ces interventions de conception peu coûteuses ont en effet le potentiel de susciter une attention involontaire, augmentant ainsi le nombre perçu de poubelles. Cette étude est une illustration éloquente de la manière dont les expériences en laboratoire peuvent constituer une première étape importante avant de se rendre sur le terrain ; nous estimons dans quelle mesure un changement de couleur des sacs poubelles augmente la visibilité des poubelles à Paris. À cette fin, nous appliquons des techniques standard de détection des signaux pour tester dans quelle mesure le changement de couleur des sacs poubelles, du gris au rouge, affecte les taux de détection des sujets. Dans trois études préenregistrées (N = 922), nous constatons que le passage de la couleur des sacs poubelle du gris au rouge se traduit par une augmentation de 28% du nombre perçu de poubelles. Cela signifie qu'un changement de couleur de sac poubelle du gris au rouge, sans coût, équivaut à l'installation de 8 400 poubelles supplémentaires dans la ville de Paris, en termes de densité perçue. Des études de réplication portant sur d'autres changements de couleur montrent que le passage du gris au bleu augmente encore la visibilité des poubelles, le bleu présentant la plus forte augmentation de visibilité dans un échantillon vivant en région parisienne par rapport à un même échantillon de résidents britanniques.

Chapitre 2 : Diminuer la pollution de l'air en utilisant le feedback dans un cadre expérimental sur le terrain

Dans ce chapitre, nous abordons un autre comportement polluant et évitable

: la combustion domestique occasionnelle. En effet, l'exposition à la pollution atmosphérique est l'une des principales causes de morbidité et de mortalité dans le monde et est largement déterminée par le comportement des ménages. Pourtant, les sources et les impacts de la pollution de l'air intérieur sont encore largement méconnus et mal perçus par le public. Par exemple, bien que le chauffage au bois occasionnel soit une activité extrêmement polluante pour les utilisateurs et qu'il soit responsable de plus de 40% de la pollution par les particules en Europe, il est associé à une perception déformée et considéré comme une activité peu polluante, naturelle et saine. Le même schéma est observé avec la combustion de bougies et d'encens, deux sources importantes de PM2.5 à l'intérieur des bâtiments. Comme nous l'avons vu précédemment, le fait de surmonter le biais de saillance en fournissant un retour d'information et une comparaison sociale s'est avéré efficace pour réduire la consommation de ressources. Dans ce chapitre, nous testons si une combinaison de ces outils est efficace pour modifier le comportement de combustion, et si elle est plus efficace qu'une campagne d'information générique. À cette fin, nous avons équipé 281 ménages de micro-moniteurs et les avons répartis en trois groupes : le groupe de traitement *Information*, le groupe de traitement *Information + Profil d'émission personnalisé* et le groupe témoin. Le traitement *Information* consistait en des dépliants hebdomadaires contenant des informations génériques sur les risques liés à la pollution de l'air intérieur et aux activités de combustion multiples, avec une attention particulière pour le chauffage au bois. Les ménages participant au traitement *Information + Profil d'émission personnalisé* ont quant à eux reçu les mêmes informations génériques ainsi qu'un profil d'émission personnalisé hebdomadaire sur leurs niveaux de pollution intérieure, constitué du graphique des relevés précis de la concentration de PM2.5 mesurée toutes les cinq minutes au cours de la semaine précédente, ainsi que des statistiques permettant de comparer leurs émissions à celles de ménages similaires. Nous constatons que le traitement *Information + Profil*

d'émission personnalisé a permis de réduire les niveaux de PM2.5 à l'intérieur des habitations de 20%, un indicateur du changement de comportement des ménages en matière de pollution, avec une diminution soutenue et significative à partir de la troisième semaine après le début de l'intervention. L'analyse de l'impact hétérogène révèle que l'effet est concentré sur les ménages les plus pollués. Pour ce groupe, le nombre de jours de dépassement de la limite OMS de 24 heures - à ne pas dépasser plus de 3 jours par an - a diminué de 52 %, passant de 12,4 à 5,9 jours sur la période d'étude. En revanche, nous n'avons observé aucun changement dans la qualité de l'air intérieur pour les ménages recevant le traitement *Information*, ce qui suggère qu'une information générique sur les risques sanitaires des activités de combustion n'est pas suffisante pour induire des changements de comportement. Ces résultats présentent un intérêt particulier pour les décideurs politiques dans un contexte où les technologies de micro-capteurs qui détectent les niveaux de PM2.5 ambiants sont de plus en plus disponibles et abordables. Pour comprendre les mécanismes à l'origine de ces résultats, nous avons recueilli des données sur la perception, les connaissances et les attitudes des ménages concernant les sources de pollution intérieure. Nous constatons que les deux interventions ont réussi à augmenter la perception de l'impact négatif du chauffage au bois et du tabagisme sur la pollution de l'air intérieur et extérieur, et à diminuer la fréquence à laquelle les ménagent déclarent utiliser le chauffage au bois à l'avenir. Nous ne trouvons aucune preuve d'un impact sur la perception du risque sanitaire de la pollution, sur les attitudes envers la réglementation du chauffage au bois, sur le plaisir d'allumer un feu, ni sur l'intention de changer d'équipement de chauffage au bois à l'avenir. La fréquence déclarée des activités de combustion n'est pas différente entre le groupe témoin et les deux groupes de traitement, de même que l'activité d'amélioration de la qualité de l'air, ce qui est en contradiction avec la réduction objective de la concentration de PM2.5 observée par les micro-moniteurs. Ce chapitre apporte plusieurs contributions à la littérature.

Premièrement, il ajoute aux preuves jusqu'ici limitées de l'utilisation des compteurs intelligents pour modifier les comportements. Deuxièmement, il fournit des preuves - encore rares dans la littérature - de la supériorité de l'information personnalisée pour changer les comportements, par rapport à la communication générique. Très peu d'études comparent l'une à l'autre, et les deux à l'absence d'information, comme nous le faisons dans cet article. Enfin, ce résultat enrichit la littérature sur le fossé entre la prise de conscience et le comportement, où les individus sont conscients d'un problème, comme le changement climatique, la pollution de l'air, ou l'importance des comportements préventifs, mais ne prennent pas de mesures concrètes.

Les êtres humains façonnent l'environnement qui les entoure, mais l'environnement physique façonne, à son tour, la psychologie humaine. L'environnement dans lequel les gens grandissent et vivent influe leur comportement et les modifications de l'environnement physique peuvent avoir des effets importants sur leurs actions. Les gens se soucient davantage du changement climatique et font plus de dons à des causes environnementales lorsque les températures locales sont élevées (Li, Johnson and Zaval, 2011) et, inconsciemment, ils produisent moins de déchets lorsqu'ils sont exposés à l'odeur du citron, suivant ainsi un parcours cognitif allant de la perception olfactive au comportement (Holland, Hendriks and Aarts, 2005). L'écologie a des répercussions encore plus profondes sur les préférences. Les enfants qui grandissent en passant plus de temps dans la nature se comportent de manière plus pro-environnementale à l'âge adulte (Chawla and Derr, 2012).
La deuxième partie de cette thèse se concentre sur une autre source d'hétérogénéité en écologie ; la pauvreté. En effet, la pauvreté et les conditions économiques difficiles affectent profondément la psychologie, les préférences et les stratégies des individus (Haushofer and Fehr, 2014). Les individus vivant dans des environnements

avec des horizons temporels plus courts pourraient choisir d'investir encore moins que les autres dans les résultats futurs, ce qui pourrait les conduire à adopter des comportements moins favorables à la conservation. Le chapitre 3 de cette thèse explore cette hypothèse médiatrice pour tenter d'expliquer la corrélation négative entre le statut socio-économique et le pro-environnementalisme. Enfin, nous pensons que les personnes vivant dans des environnements pauvres en ressources peuvent également réagir différemment aux politiques publiques. Le chapitre 4 est une analyse suggérant que les antécédents socioéconomiques peuvent modérer l'efficacité des interventions comportementales environnementales couramment employées - tels les choix par défaut, la comparaison sociale et les dispositifs d'engagement - qui s'appuient sur des biais susceptibles d'être hétérogènes entre les differents niveaux de revenus.

Chapitre 3 : L'impact du statut socio-économique sur l'environnementalisme

Comme nous l'avons mentionné plus haut, les individus orientés vers le futur ont tendance à afficher des attitudes et des comportements plus favorables à l'environnement, par rapport à ceux qui sont orientés vers le présent. L'étude des déterminants des préférences temporelles pourrait donc éclairer les facteurs qui influencent également l'environnementalisme. Le statut socio-économique (SSE) est un facteur clé dans la détermination des préférences temporelles. Il est important de noter que le statut socioéconomique est également positivement corrélé à la volonté d'agir pour l'environnement. Dans cet article, nous vérifions en trois études si les préférences temporelles sont des médiateurs partiels à la relation entre le statut socioéconomique et le pro-environnementalisme. Dans la première étude, nous avons

testé l'hypothèse selon laquelle les attitudes pro-environnementales sont positivement corrélées avec le SSE sur un large échantillon transversal français. Nous trouvons les résultats attendus à la fois avec une mesure objective et subjective du statut socioéconomique. Ensuite, nous avons mené une étude en ligne comprenant une tâche d'actualisation temporelle, qui nous a permis de tester pleinement l'hypothèse de médiation sur des participants britanniques. Nos résultats suggèrent que l'association positive entre le statut socioéconomique et les attitudes pro-environnementales est partiellement médiée par les préférences temporelles, mais aucune relation de médiation significative n'a été trouvée pour le comportement pro-environnemental. Enfin, pour vérifier l'existence d'une relation causale, nous avons mené une expérience en laboratoire inspirée par des recherches antérieures montrant qu'il est possible d'utiliser des informations sur le revenu comme traitement expérimental, de manière à modifier la perception de la condition socio-économique d'une personne. Dans cette expérience, nous avons recruté uniquement des participants qui sous-estiment leur position dans la distribution des revenus. Dans le groupe de traitement, les participants ont reçu une correction de leur perception erronée, afin d'augmenter leur revenu relatif perçu, tandis que le groupe de contrôle n'a reçu aucune intervention. Les participants ont ensuite répondu à une tâche d'actualisation du temps et à des questions mesurant le pro-environnementalisme. Bien que l'évolution attendue vers une augmentation des préférences pour l'avenir n'ait pas été observée, nous avons trouvé un effet modéré du traitement sur le pro-environnementalisme.

Chapitre 4 : L'impact du revenu sur l'efficacité des interventions comportementales

Si nous pensons que des écologies différentes produisent des stratégies cognitives

différentes, devons-nous nous attendre à ce que les ménages à faibles revenus réagissent différemment à une politique publique comportementale tirant parti des biais cognitifs? Si l'efficacité de l'architecture de choix est bien documentée, nous en savons beaucoup moins sur ses conséquences potentielles en matière de redistribution. Dans ce chapitre, j'examine trois des interventions les plus documentées en matière de politique publique environnementale : la fixation d'objectifs, les options par défaut et la comparaison sociale. J'analyse comment les biais et les leviers cognitifs qui sous-tendent leur efficacité, tels que l'orientation vers l'avenir, le biais d'inertie et la conformité sociale, varient selon les niveaux de revenu et je passe en revue les preuves de l'hétérogénéité de leurs effets dans la littérature. Je constate que, bien que les preuves solides soient encore rares dans le contexte environnemental, les politiques publiques comportementales pourraient avoir des effets distributifs involontaires et aggraver les disparités sociales existantes. Des recherches supplémentaires pourraient tenter d'explorer et de combler les lacunes de la littérature sur les effets hétérogènes et distributifs des interventions comportementales, notamment les messages de normes sociales génériques.

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